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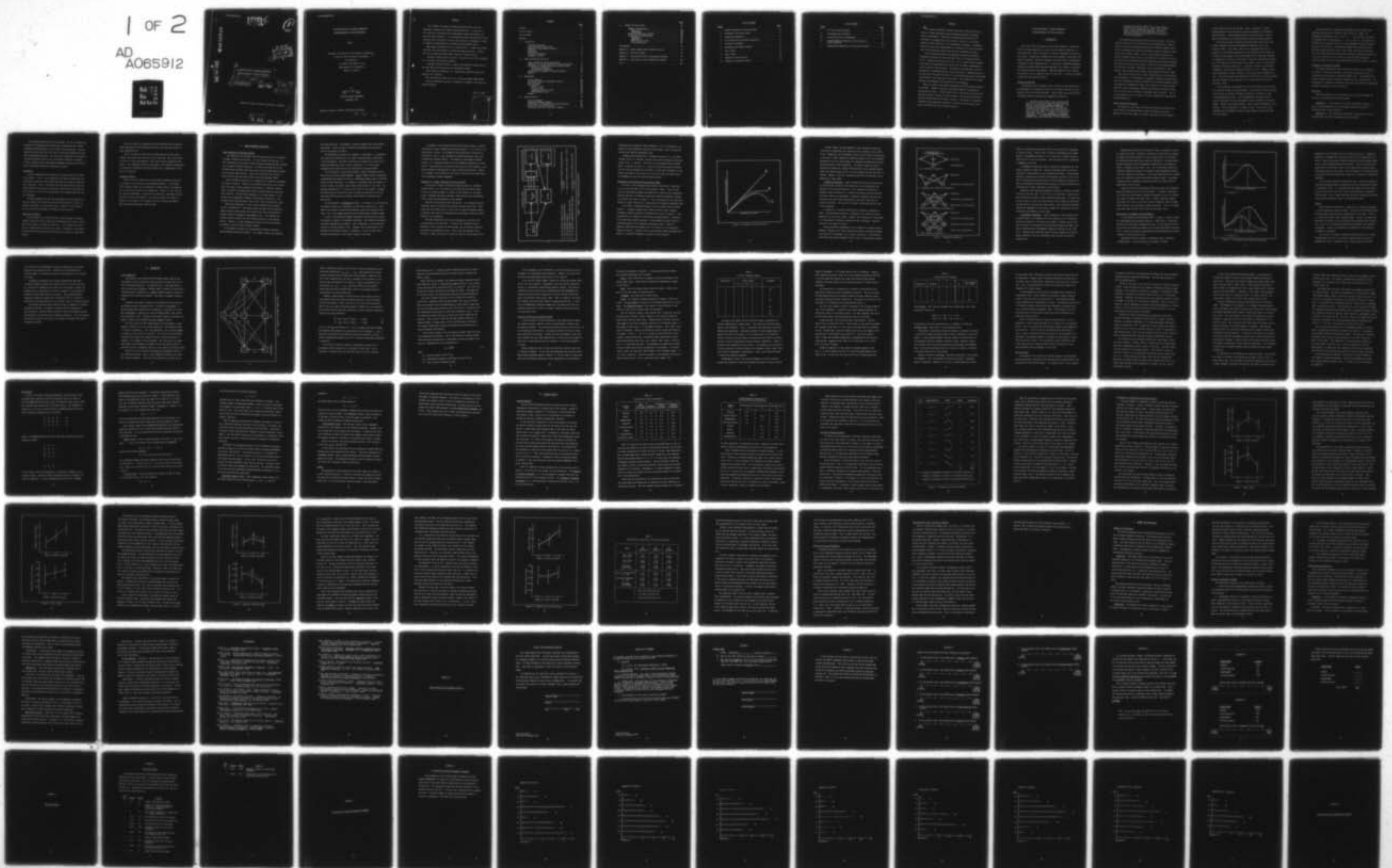

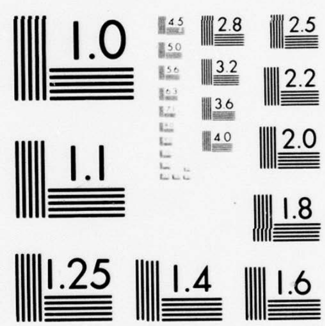

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(6) AN INVESTIGATION OF A HUMAN INFORMATION PROCESSING MODEL FOR DECISION MAKING.

(9) Master's THESIS,

(14) AFIT/GSM/SM/78S-23

(10) David R. Unger
Capt USAF

(11) Sep 78

(12) 119p.

Approved for public release; distribution unlimited.

AFIT/GSM/SM/78S-23

AN INVESTIGATION OF A HUMAN INFORMATION PROCESSING MODEL FOR DECISION MAKING

THESIS

Presented to the Faculty of the School of Engineering

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the

Requirements for the Degree of

Master of Science

by

David R. Unger, B.S.
Capt USAF

Graduate Systems Management

September 1978

Approved for public release; distribution unlimited.

Preface

This research into human information processing was, from the beginning, a venture into largely uncharted territory. It was not at all clear how to proceed with the experimental design and analysis, or what the results would be. It is my hope that others may be able to build upon this work, correcting its faults and refining its strengths, in order to expand our understanding of the human decision-making process.

Many people contributed to this research effort. Foremost were those individuals who participated in the decision-making exercise. I would also like to thank those with whom I worked on a personal basis:

Lieutenant Colonel Adrian M. Harrell, my advisor, who first introduced me to the topic and guided my progress;

Lieutenant Colonel William C. Letzkus, who generously shared with me the data upon which the exercise was subsequently based;

Major Charles W. McNichols, III, whose advice regarding statistical analysis was invaluable;

Miss Joyce Wilson, whose skills as a typist are deeply appreciated;

and most importantly, my wife, Elizabeth, my toughest critic and most patient supporter.

David R. Unger

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Abstract

This research examined information overload in decision makers by means of a human information processing model developed by Schroder, Driver, and Streufert. That model provided that the ability of an individual to integrate data into a decision varied in a curvilinear fashion with the complexity of the information environment. Information processing capacity was hypothesized to increase up to a certain optimum level and then decrease, marking the onset of information overload.

A policy capturing exercise was employed to measure the amount of information processed for three different levels of information availability. Subjects were given sets of four, six, or eight national problem areas along with hypothetical priorities that the federal government was said to attach to those problems. The subjects indicated their levels of agreement or disagreement with each set of priorities. Regression analysis was then used to discover how many of the available problem areas contributed significantly to the three sets of decisions. The information utilization patterns were compared to the predictions of the model.

About 21 percent of the sample displayed the type of pattern predicted by the model. Another 29 percent consistently used more information as more became available. A discriminant analysis conclusively classified the remaining subjects into one of the two groups: one for which information overload occurred and one for which it did not. The amount of information processed by both groups was identical at the four- and six-factor input levels, differing only after overload occurred.

AN INVESTIGATION OF A HUMAN INFORMATION PROCESSING MODEL FOR DECISION MAKING

I. INTRODUCTION

One of the resources essential to the modern manager is information. The size of many organizations, as well as the range and complexity of their operations, limits the amount of first-hand knowledge any one person can acquire. Consequently, managers have come to depend increasingly upon reports, summaries, financial statements, and other forms of systematized information as decision-making aids. In some cases, automated management information systems (MISs) have been developed in an attempt to keep pace with multiplying data requirements. Whether automated or not, however, the objective of any information source is the same: to enable the manager to make decisions more effectively.

Information Overload

Particularly since the advent of MIS, concern has been mounting over the phenomenon of information overload, or the adverse effects of large amounts of data on the decision maker. Ackoff (1967) aptly described the information overload problem from a managerial perspective:

> Most MISs are designed on the assumption that the critical deficiency under which most managers operate is the lack of relevant information. I do not deny that most managers lack a good deal of information they should have, but I do deny that this is the most important informational deficiency from which they suffer. It seems to me that they suffer more from an over abundance of irrelevant information. ...My experience indicates that most managers receive much more data (if not information)

> than they can possibly absorb even if they spend all of their time trying to do so. Hence, they already suffer from an information overload. They must spend a great deal of time separating the relevant from the irrelevant and searching for the kernels in the relevant documents.

The misgivings expressed by Ackoff were well-founded. Quite apart from the nuisance of the filtering process the managers must conduct, a number of studies have demonstrated that the information handling abilities of individuals were actually inhibited by excessive amounts of data (Driver and Streufert, 1969). That is, people began to partially or totally disregard certain inputs as the quantity of information increased. This facet of the information overload problem has generated considerable discussion and research, particularly in the field of accounting (Dermer, 1973; Miller, 1972; Mock, 1969; Mock, Estrin, and Vasarhelyi, 1972; Revsine, 1970; Streufert and Schroder, 1965; Suedfeld and Driver, 1965).

Much could be gained from a clearer understanding of how information overload operates. The designers of management information systems would more fully appreciate the need to streamline and simplify automated reports. Increased use of mathematical models and simulations for certain complex decisions could be encouraged. Managers and executives themselves might learn to assess their information requirements more accurately. The key to these benefits lies in finding a practical technique for analyzing the problem empirically.

Human Information Processing

One approach to the study of information overload has been derived from a branch of psychology known as human information processing. Research in that field sought to discover "how people put data together

in making decisions" (Driver and Mock, 1975). In essence, it took a systems approach to decision-making, viewing individuals as information processing units. Decision-making behavior was interpreted in terms of inputs (information) and resulting outputs (actions or other outcomes).

One particular human information processing model that directly predicted information overload was developed by Schroder, Driver, and Streufert (1967). Their model, which will be described more fully in Chapter II, associated the complexity of the information that entered the "system" with the degree to which the separate bits of data were combined, or integrated, to arrive at the decision. These two variables were related by a bell-shaped curve which peaked at the center. Thus, as the incoming information grew more complex (e.g., increased in volume or arrived more frequently), the degree of integration would first rise. However, beyond some optimum point, further increases in input would cause integration to fall. The resulting decisions reflected less efficient use of the available data and, therefore, were expected to be of lower quality (Driver and Streufert, 1969).

The link between the Schroder-Driver-Streufert model and the information overload concept was straightforward. The onset of overload coincided with the point of optimal information integration, worsening as input increased beyond that point. This suggested that the model could be applied successfully to the experimental study of information overload in humans. However, one problem remained: how to measure the degree of integration. This has been done in a number of ways. The research effort documented here attempted to employ a process known as policy capturing for this purpose.

Policy capturing as a technique for modeling decision patterns was developed from the work of Brunswik (1952) and Hoffman (1960). By mathematically analyzing a set of decisions, a linear equation consisting of weighted sums of the appropriate variables is derived. The weights are adjusted so as to provide the best possible agreement between the equation and the actual decisions. Although the Schroder-Driver-Streufert model had been tested extensively prior to this study, there was no indication that policy capturing had ever been used to measure information integration. It was this observation, plus a desire to test the human information processing model, that led to the experiment upon which this report is based.

Statement of the Research Problem

The problem toward which this research was directed was to determine the impact of information overload on individual decision-making and to investigate human information processing capabilities. The Schroder-Driver-Streufert model provided a practical framework for this investigation. The measurement of information integration required by that model was accomplished through the technique of policy capturing.

Objectives

The primary objective of the research was to test two hypotheses set forth by the Schroder-Driver-Streufert model:

Hypothesis 1. As the amount of available information increases, a point is reached beyond which the individual decreases the amount of information used to reach a decision.

Hypothesis 2. Some individuals consistently incorporate more of the available data into their decision-making than do others.

Two secondary objectives were also pursued. One was to examine the feasibility of employing policy capturing in conjunction with a human information processing model in the study of decision-making. This was especially significant since this type of application apparently had not been investigated previously. The other was to determine to what degree information processing ability was correlated to measures of academic ability (Graduate Record Exam/Graduate Management Admission Test scores) and/or achievement (cumulative grade point average).

Assumptions

Certain assumptions which governed this research need to be stated at the outset. First, it was assumed that the decisions made under the experimental conditions would approximate those that would be reached in real situations. That is, individual decision-making behavior would not change radically just because the subjects knew they were participating in an exercise. At least one study (Brown, 1972) demonstrated that this was reasonable.

A second assumption was that the experimental decision would be one that the subjects were qualified to make and would require at least an attempt to consider all the available data. Chapter III will describe how the exercise was designed to incorporate these qualities.

Scope and Limitations

This experiment was carried out among a selected group of graduate students from the Air Force Institute of Technology (AFIT) School of Engineering and School of Systems and Logistics. It is unlikely that such a group is representative of society as a whole. Consequently, care should be exercised before applying the findings of this research to other populations.

Also, this study was concerned only with individual decision-making. Group processes were not addressed and may not yield the same results as those documented here.

Lastly, it should be noted that, although the exercise was rather lengthy, the range of decisions was fairly restricted. Only three different levels of input were examined. Also, each variable assumed only two values. This experiment should be considered a first attempt to understand the workings of information processing rather than a comprehensive treatment of the subject.

Subsequent Chapters

Chapter II of this report will discuss human information processing as an approach to the study of decision-making behavior. The Schroder-Driver-Streufert model will be presented in greater detail, with emphasis on its underlying concepts and its hypotheses. Chapter III will describe the research methodology, including policy capturing, experimental design, and data collection and analysis. The research results will appear in Chapter IV, and Chapter V will summarize the key findings and present implications and conclusions from the study.

II. HUMAN INFORMATION PROCESSING

Human Information Processing Concepts

The Schroder-Driver-Streufert model provides one basis for interpreting human information processing. It is by no means the only one. In fact, approaches to the study of human information processing have branched out in several different directions. The unique contributions of the Schroder-Driver-Streufert model may be more clearly appreciated by comparison with these other branches. Much of the discussion that follows is drawn from the excellent review article by Driver and Mock (1975).

Human information processing is a subdivision of cognitive psychology, the study of thinking. Research into cognition historically has pursued one of two goals, either normative or descriptive. Normative research seeks to establish how *well* people think or decide based upon some specified criterion. The descriptive approach, as its name implies, is concerned only with *how* those thoughts or decisions are arrived at. The Schroder-Driver-Streufert model clearly falls into the descriptive class.

Descriptive techniques, in turn, may be characterized as general, unique, or differential. The general school presumes that the decision-making processes people employ are basically the same, and differences between them can be charged to experimental error. This approach has yielded valuable insights into the thinking processes of the "average person." However, it cannot adequately account for variations between individuals, which are often of major interest.

At the opposite extreme, the unique approach examines individual decision-making processing in detail. This permits analysis and modeling

with high precision. Its drawback is that such models hold little general application. Little of what is learned from one person can be used to explain the behavior of others.

The differential approach lies somewhere in the middle. It recognizes that people are different but still exhibit some underlying similarities in decision-making. Individual variations are treated not as error but as predictable departures from a central regularity. It is this second assumption which characterizes the Schroder-Driver-Streufert model.

The third means of classifying research in human information processing has to do with the method employed. Value-oriented research concentrates on determining the subjective values or preferences people place on different aspects of decision-making. For example, a researcher might ask whether, in a given setting, the subject would prefer receiving more or less data. The attitude questionnaire is a typical vehicle used in this method. Although the results may be instructive, there is always the possibility that attitudes and opinions may not accurately reflect what an individual would actually do.

The other method is performance-oriented. Its purpose is to discover how individuals actually use information, not how they say they use it. Thus, results are anchored in objective performance rather than subjective attitudes. This is the method employed by the Schroder-Driver-Streufert model.

Finally, the differences between information processing styles may be attributed to a number of information dimensions. Each dimension represents a different perspective on behavior. One is ambiguity, or the uncertainty inherent in the data (Dermer, 1973). Another, the one applicable to the Schroder-Driver-Streufert model, is complexity. As will be seen later, information complexity is the central concept of the model.

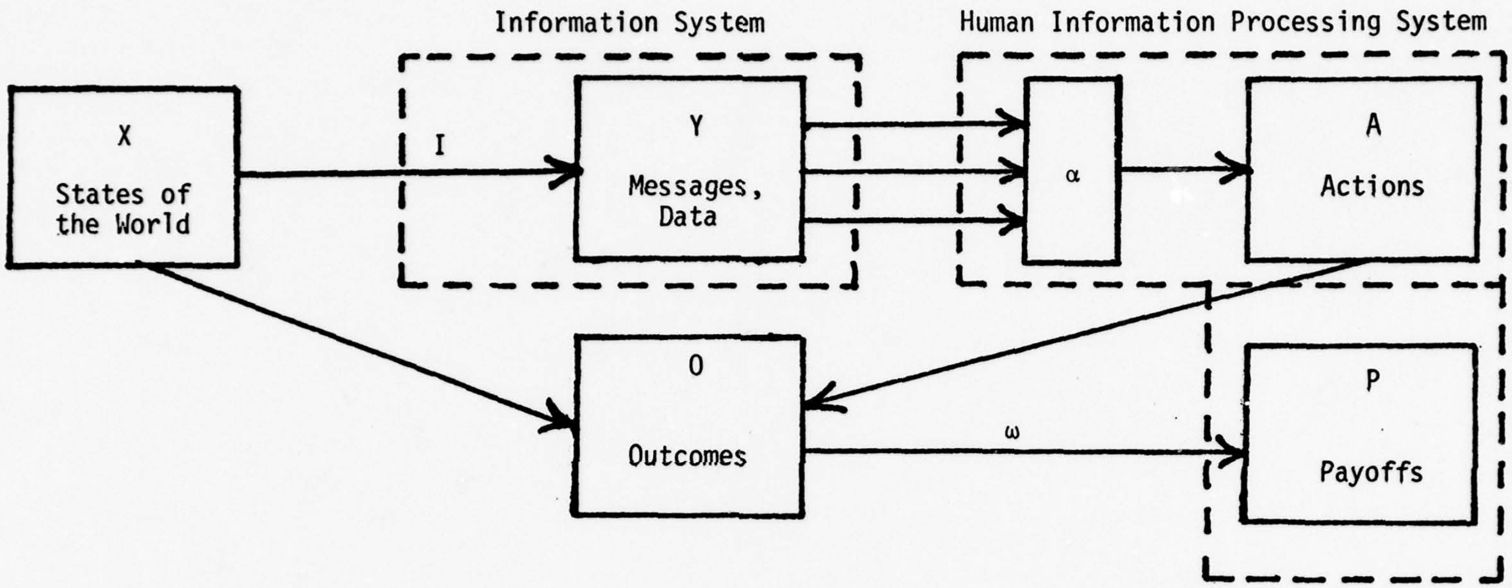
To summarize, the Schroder-Driver-Streufert model occupies a specialized branch of human information processing research. It is, first of all, descriptive in nature. Its assumptions about behavioral variations are differential; that is, they represent anticipated departures from a generalized core response pattern. Its methods are performance-oriented. Finally, it is concerned primarily with the complexity dimension of information. These qualities are noted to stress the fact that the model is not being presented as the approach to human information processing. Rather, it is offered as one alternative that seems to have particular application to the problems of modern management.

Components of a Human Information Processing System

A discussion of human information processing would be inadequate without placing it in the context of the whole decision-making system. In fact, the systems concept is central to the character of the model. Figure 1 (adapted from Driver and Mock, 1975) portrays the relationships of the various system components to one another.

Note that two subsystems enter the process. The information system interprets states-of-the-world and produces messages about them. These range from very simple aural or visual cues to complex automated reports. In general, each state will generate multiple messages reflecting several dimensions of information.

The human information processing system *per se* is entirely self-contained within the individual. It accepts the information system messages as input, operates on them through a set of decision functions, and selects an appropriate action. Later, after the outcome of the decision is known, the payoff or subjective value of that outcome to the



X = Set of relevant states of the world

Y = Set of messages (information) about X

A = Set of possible actions a

O = Set of outcomes o (one for each X-A pair)

P = Set of payoffs p associated with each outcome

I = An information relation relating states and messages

α = A decision function (rule) such that $a = \alpha(Y,I)$

ω = A utility or preference function such that $p = \omega(o)$

Figure 1. A Human Information Processing System

individual may be noted for future reference. This is illustrated as an adjunct to the information processing system proper, since it may modify the decision function subsequently used.

Leaving aside the question of information accuracy (i.e., the effectiveness of the "I" relation), the key to the human information processing system is the α function. The thrust of the Schroder-Driver-Streufert model is that the structure of α varies not only from person to person, but also from one message set to another. It holds that information is not simply acted upon by the system, but in turn acts upon the system itself to fundamentally alter the decision-making process.

Background of the Schroder-Driver-Streufert Model

The roots of the Schroder-Driver-Streufert model may be traced back as far as the late 1950's (Driver and Streufert, 1969). Prior to that time, the relationship between the complexity of input and the information handling capacity of information processing systems was generally assumed to be linear (see curve A, Figure 2). Thus, the capacity of the system was thought to expand indefinitely to keep pace with increased information load.

In the 1950's, researchers began to notice an upper limit to system capacity. It began to appear that, after an initial linear response, information handling leveled off asymptotically (curve B, Figure 2). This characteristic was observed in individual and group behavior. Eventually it was found that further increases in input complexity often resulted in diminished capacity for information processing (curve C, Figure 2). Examples ranged from the response rates of retinal cells to the musical output of pianists. Schroder, Driver, and Streufert (1967) developed their model as a conceptual framework to account for this behavior.

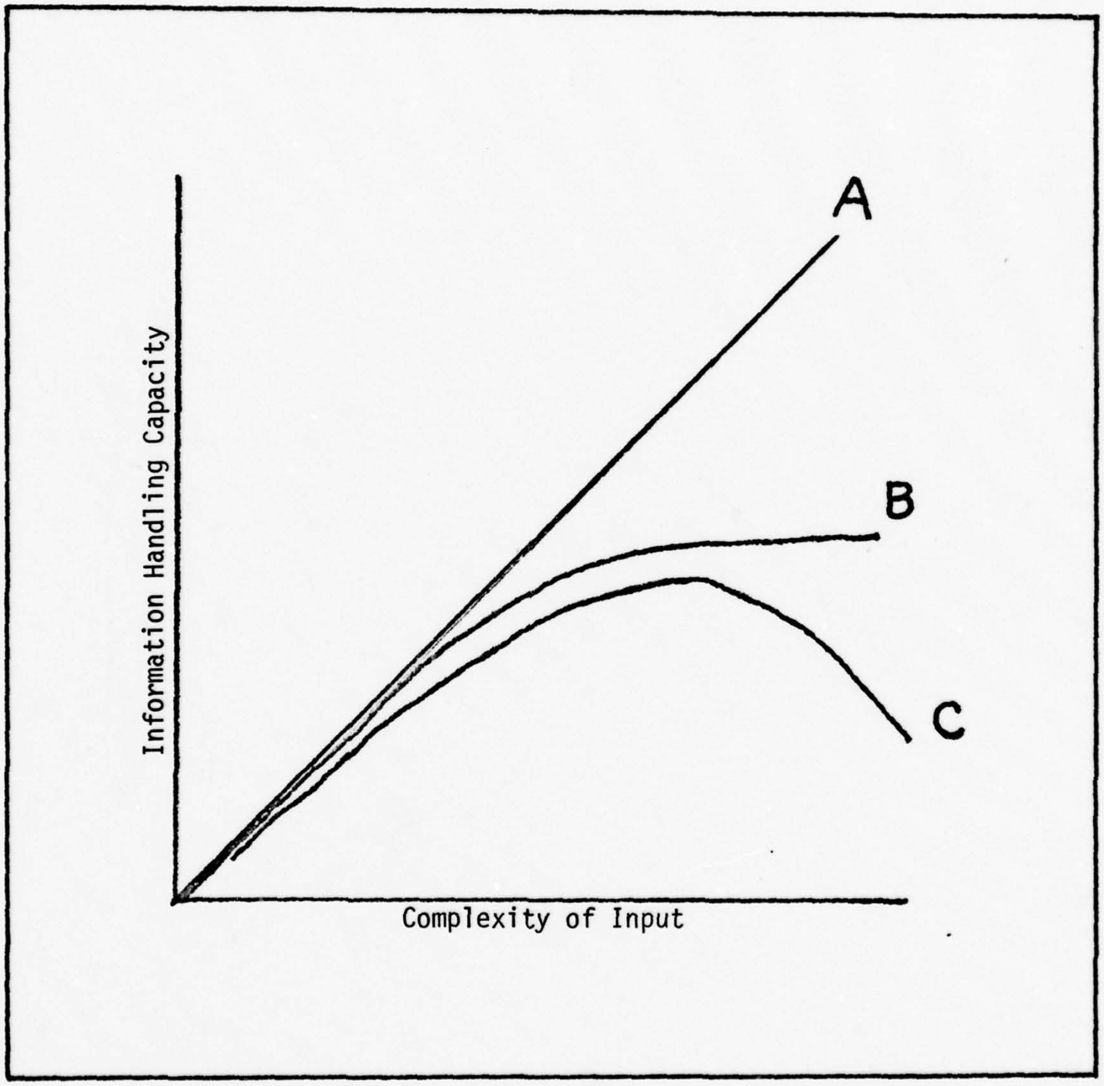


Figure 2. Information Utilization Curves

In their scheme, the key elements of human information processing structures are dimensions and integrating rules (Schroder, et al, 1967:7, 14-23). Dimensions are the elemental units by which stimuli are perceived. In the case of light, appropriate dimensions might be color and brightness. Integrating rules are simply methods of combining and comparing the values measured on each of those dimensions. The extent to which an input is analyzed into dimensions, termed differentiation, varies markedly between humans and simpler organisms and to a lesser degree from one individual to another. However, it was the integrative qualities that Schroder, et al, emphasized in their model.

Integrative Complexity. Human information processing structures may be characterized according to the complexity of the integrating rules applied to the perceived dimensions. This integrative complexity, as Schroder, et al, referred to it, reflects the creativity and flexibility with which inputs are interpreted. Integrative complexity may vary continuously from low to high, representing a transition from rigid to abstract structures. The next set of figures illustrates how this transition progresses.

In Figure 3a, a structure exhibiting low integrative complexity is shown. The individual perceives an information unit along one or more dimensions (in this case, three). However, the information is interpreted in a fixed manner; alternative meanings are not considered. Cognitive rigidity is the order of the day.

Certain behavioral consequences of low integrative complexity may be expected. Because of the rigid interpretive process, the perceived dimensions tend to be dichotomous (e.g., yes/no, true/false). Finer distinctions than these would contribute little to such a fixed decision process.

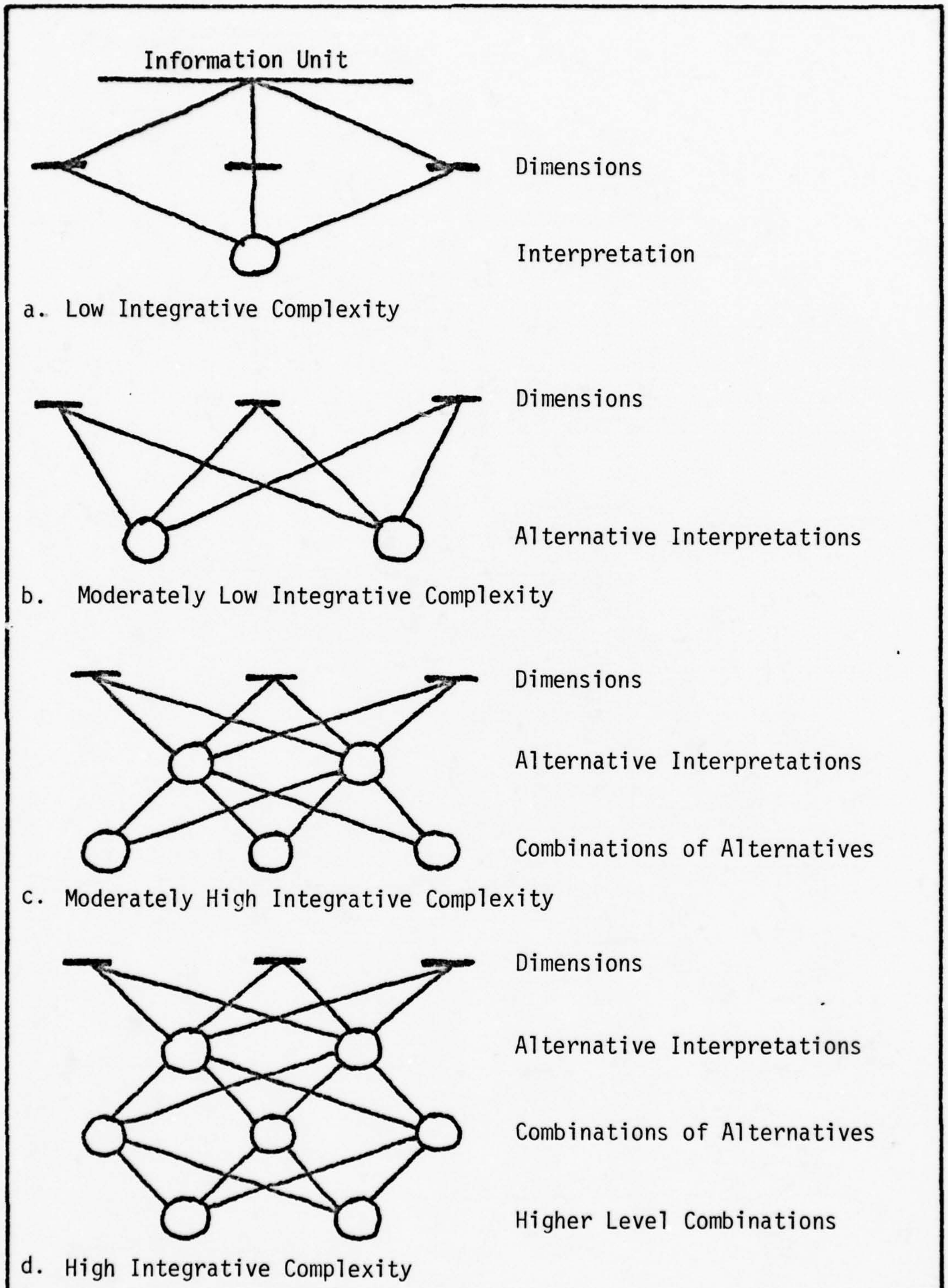


Figure 3. Integrative Complexity

Conflict is minimized and resolved quickly by the exclusion of ambiguous or contrary inputs. Finally, when a previous interpretation must change because of overwhelming evidence, it will often do so abruptly through a massive shift in the rule structure. Then the new position is maintained as doggedly as the first.

A fundamental change takes place in moving to a moderately low integrative complexity (Figure 3b). Here the individual begins to perceive alternative interpretations to the information presented. Choice becomes necessary, lessening the rigidity of the previous structure. Still, this form of information processing retains a certain degree of inflexibility. Once the interpretive scheme has been selected, the other alternatives are discarded and no longer contribute to the decision.

Moderately high integrative complexity (Figure 3c) extends structural flexibility one more step. At this level, the individual is able to combine alternatives instead of simply choosing between them. In effect, two or more "points of view" can be perceived at once, compared to each other, and the effects of one upon the other traced. High integrative complexity (Figure 3d) represents an even greater capability to generalize from and interrelate the dimensions of the input.

Environmental Complexity. The key attribute of the Schroder-Driver-Streufert model is the hypothesis that the complexity of an information processing structure is not fixed, but variable. Schroder, *et al*, held that the factor that determined the system (and thereby the output) integrative complexity was environmental complexity (Schroder, *et al*, 1967: Ch 3). Although they identified several possible components of environmental complexity, only one—information load—concerns the research reported here.

Information load refers to the amount of data an individual receives in a given time frame. Information load may be varied either by changing the number of inputs provided in a fixed length of time or by altering the time period over which those inputs are delivered. The relationships between information load and integrative complexity are illustrated in Figure 4 (Schroder, et al, 1967:37, 40). For an individual (Figure 4a), integrative complexity reaches its maximum at some intermediate information load. When the environment is less or more complex than this optimum case, the information processing structure becomes simpler. At optimum information load, information processing reaches its highest state of organization and efficiency.

Figure 4b reflects the postulated difference between the information processing characteristics of two individuals. In general, some people will exhibit uniformly greater integrative complexity across all information loads, as shown by the upper curve. Further, these more complex individuals will tend to reach their optimum information loads at higher levels than will the consistently simpler processors. That is, the upper curve will "peak" further to the right than the lower curve.

Application of the Model to Decision-Making

If the Schroder-Driver-Streufert model is correct, it offers a means for understanding decision-making behavior. Specifically, it provides a mechanism for explaining information overload. If the concepts of information load and integrative complexity can be given measurable interpretation, it should be possible to experimentally determine where the optimum information processing point lies.

Operationalizing the concept of information load is relatively straightforward. It may be equated to the number of factors

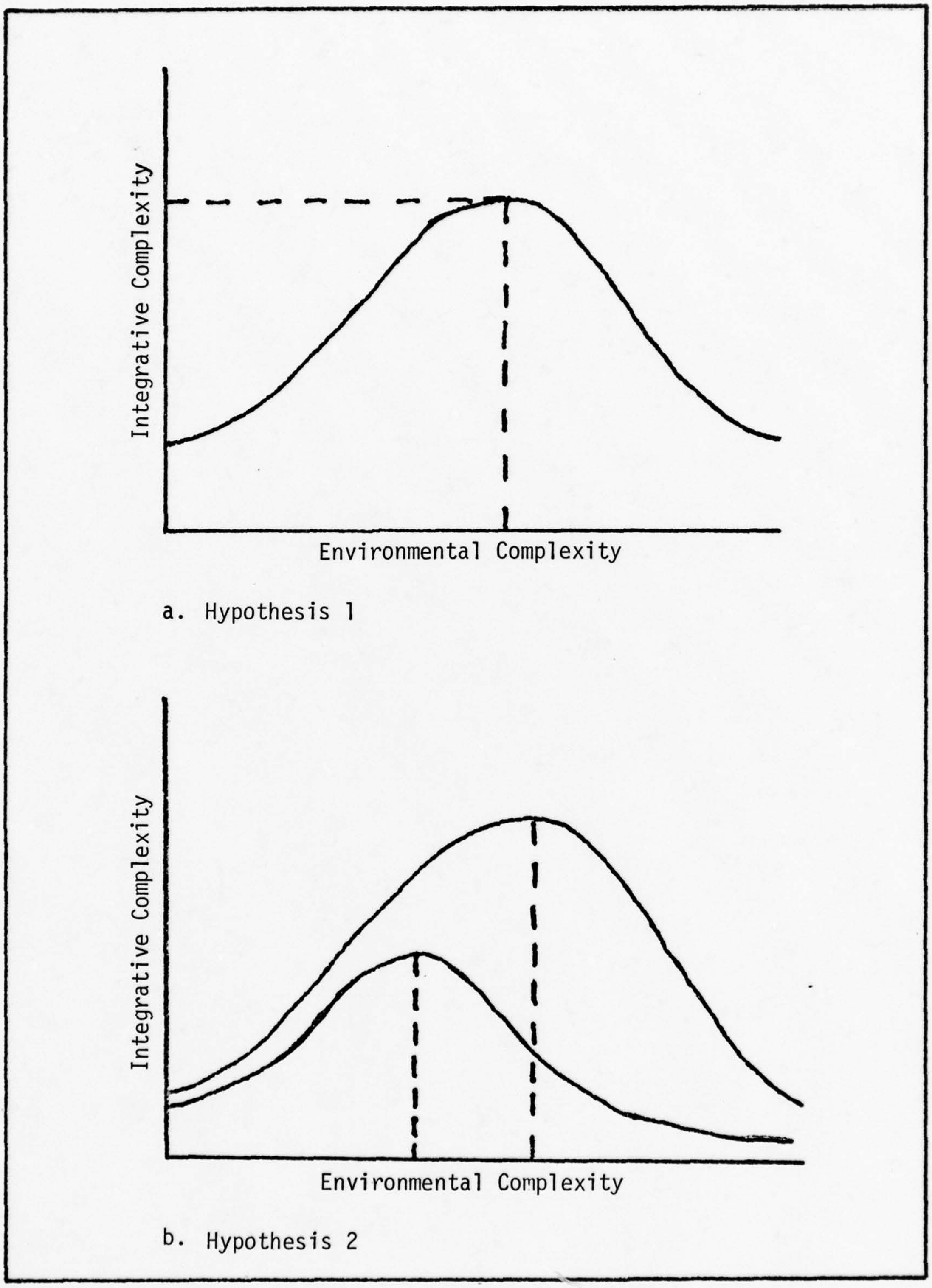


Figure 4. The Schroder-Driver-Streufert Hypotheses

presented to the individual for use in reaching a decision. Integrative complexity is somewhat more involved but may still be represented fairly easily. Recall that maximum integrative complexity implies maximum organization of the information processing structure. Such a structure should permit more of the available input to pass through the system and have a significant effect on the outcome. Thus, the number of information factors utilized by the decision-maker may be taken as an indicator of integrative complexity.

With the above operational definitions, then it should be possible to construct experiments wherein information use can be measured and related to information input. It is expected that the number of factors contributing to the decisions will rise, peak, and then decline as information load increases. Thus, a model based upon the human information processing concept could represent the onset of information overload.

Summary

Human information processing, a subdivision of cognitive psychology, is itself divided into several branches. The place of the Schroder-Driver-Streufert model among them can be characterized in four ways. First, it is a descriptive rather than a normative model. Second, it assumes that behavioral variations are real differences but consistent with a general law. Third, it is concerned with objective performance, not subjective preferences. Fourth, it concentrates on complexity as the predictive component of information.

The function of a human information processing system is to accept messages about the state of the world, interpret them, and select an appropriate action in accordance with an internal decision function.

This function may be subsequently altered by knowledge of the outcome produced by the selected action. According to the Schroder-Driver-Streufert model, it also may be altered by the complexity of the information input.

The model was developed after research demonstrated that human information handling capabilities tended to level off and then decrease as a function of information load, after first displaying a steady rise. Schroder, et al, explained this in terms of changes in the integrative complexity of the human cognitive structure. They hypothesized that integrative complexity peaked at an intermediate value of information load and that the peak would occur at different levels for different persons.

The Schroder-Driver-Streufert model provides a framework for studying information overload. The number of separate factors presented to a decision-maker is identified with information load and the number actually contributing to the decision with integrative complexity. Then, by plotting one against the other, the location of the peak will pinpoint the onset of information overload.

III. METHODOLOGY

Policy Capturing

The testing of the Schroder-Driver-Streufert model required that individuals be given information processing tasks and that their use of the information be measured. To accomplish this, a technique known as policy capturing was employed. Hoffman (1960) is generally credited with introducing policy capturing as a judgment-modeling approach, basing his formulation on a portion of Brunswik's lens model of judgment (Brunswik, 1952).

Brunswik's lens model is based on the assumption that the decision environment provides information that is uncertain and ambiguous. A decision-maker must interpret this information in a way that will prove most advantageous in dealing with that environment (Beach, 1967; Slovic and Lichtenstein, 1971). Brunswik's lens model (Figure 5) represents the manner in which the environment and human judgment interact.

The left side of the lens diagram depicts the environment, or what Chapter II referred to as the state-of-the-world. The particular state of interest is denoted Y_e. This state generates a set of cues (messages) X_1 through X_n that reflect its qualities. The right side of the figure represents the subject, who combines the cues to reach a decision or judgment Y_s in response to the environment. The cues serve as an interface between the environment and subject and are the means by which an individual collects information, much as a lens collects and focuses light.

Typically, the cues and the corresponding environmental state will not correlate perfectly. That is, the information provided by the cues will often be ambiguous. The solid lines connecting Y_e and the cues in

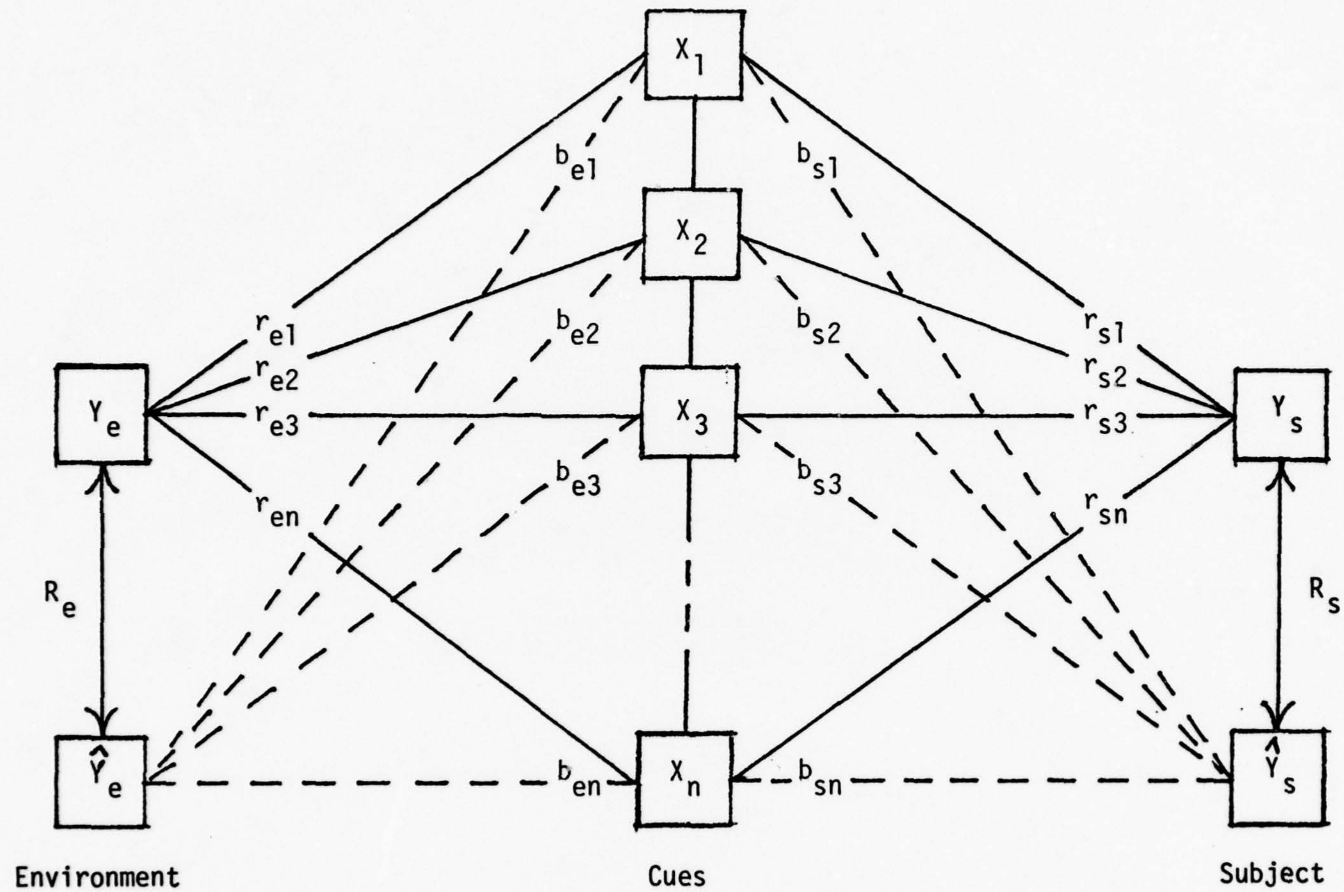


Figure 5. Brunswik's Lens Model (Beach, 1967)

Figure 5 indicate the various cue validities, which are expressed as the correlation coefficients r_{e1}, r_{e2}, ..., r_{en}. These measure the relative accuracy with which each cue describes the environment. Similarly, the solid lines connecting the cues and Y_s represent cue utilization, or how much the cues contributed to the decision. These are measured by the correlations r_{s1}, r_{s2}, ..., r_{sn}. Both the validity and utilization coefficients must be calculated from a series of environment-decision relationships, not from a single case.

Suppose a second subject is given access to the validity and utilization coefficients describing the previous behavior of the environment and the first subject. Given a new set of cues, how could the environmental state (Y_e) and/or the decision-maker's response (Y_s) be predicted? One way would involve using the coefficients to derive multiple regression equations for these quantities:

$$\hat{Y}_e = b_{e0} + b_{e1}X_1 + b_{e2}X_2 + \ldots + b_{en}X_n \quad (1)$$

$$\hat{Y}_s = b_{s0} + b_{s1}X_1 + b_{s2}X_2 + \ldots + b_{sn}X_n \quad (2)$$

In Eq (1), the b_{ek} coefficients (k = 1 to n) represent the optimal weights that minimize the variance in Y_e unexplained by the estimator $\hat{Y}_e$. This is equivalent to maximizing the multiple correlation R_e between Y_e and $\hat{Y}_e$. A similar interpretation applies to Eq (2), for which the multiple correlation is denoted R_s.

Eqs (1) and (2) provide a means for estimating the state of the environment and the response of an individual to that state. Policy capturing is concerned only with the right side of the lens, that part

described by Eq (2). It employs multiple regression analysis to derive (capture) the cue weightings (policy) that most closely reproduce the known Y_s values.

Apart from the cue weights, the regression process generates several other quantities useful in interpreting judgment policies. One of these is the squared multiple correlation $(R_s)^2$, or simply R^2. This gives the fraction of variance explained by the regression model. The higher the R^2, the more closely the model matches predicted and observed behavior.

Some other valuable quantities are the standardized regression coefficients, sometimes called the beta weights (Nie, et al, 1975:325). These are analogous to the unstandardized b_{sk} coefficients, except that the cue values have been rescaled so that each cue has a variance of one. The standardized coefficients are often more convenient to use. First, the regression constant term b_{s0} is always zero, which simplifies the equation. Also, since all cues have the same standard deviation, it becomes simpler to compare their relative contributions to the model. This cannot be done when variables are measured on different units or display different distributions.

A third useful concept is one developed by Hoffman (1960) utilizing the standardized coefficients. This is the concept of relative weight, which describes the proportion of explainable variance accounted for by each cue. Mathematically, the relationship is:

$$W_i = B_i^2/R^2 \tag{3}$$

where

W_i = relative weight of the i^{th} cue

B_i = standardized regression coefficient for the i^{th} cue

R^2 = total variance explained by model

Strictly speaking, this relationship is valid only when the cues are orthogonal, or uncorrelated among themselves. However, this restriction was met by the experimental design used in this research.

In all but the simplest models, regression calculations become highly tedious and time-consuming. Consequently, most multivariate regression analysis is performed by sophisticated computer programs. The analyses performed for this research were accomplished with the REGRESSION subprogram of the Statistical Package for the Social Sciences (SPSS) (Nie, _et al_, 1975:320-367; Cohen, _et al_, 1976). SPSS is a powerful, yet flexible, package requiring minimal computer programming expertise. In addition, the REGRESSION subprogram automatically provided the R^2 and standardized coefficients as well as a number of helpful statistical values to be described later.

Fractional Factorial Experimental Design

In the discussion of policy capturing, it was noted that the regression modeling process required a series of observations, matching cues, and subject responses. The correlations derived from those observations led to the regression coefficients. The question naturally arises as to how many observations are enough. Further, when the experimenter rather than nature chooses the cues, what combinations of values should be assigned to those cues? These questions must be answered if a valid policy model is to result.

These problems are akin to those that have been faced for some time in industrial research. It was from that background that factorial experimental design developed (Davies, 1956:Ch 7). The term takes its name from the strict and orderly selection of value combinations to be assigned to

the factors (variables) of interest. In discussing factorial designs, the following definitions will be useful:

Factor - any variable that is thought to affect the outcome of the process under study. Factors may be quantitative (temperature, length) or qualitative.

Level - one of the values that a factor can assume. Factors must have at least two levels, but may have more.

Treatment - one unique set of factor levels.

Effect - the change in outcome produced by a change in level for a factor. The main effect of a factor is the average change over all treatments. The interaction effect of two factors is the difference in the effects of the first at various levels of the second.

The full factorial design is the simplest and, in some ways, the most desirable type of design. Table I depicts a full factorial design for three factors with two levels each. (Designs where all factors have the same number of levels are frequently referred to as n^p designs, where n is the number of levels and p is the number of factors. Thus, Table I portrays a 2^3 design.) Factors are denoted by capital letters and levels by the symbols "+" and "-". The "+" is called the high level and is traditionally, though arbitrarily, assigned the larger quantitative or more positive qualitative value (e.g., yes, present, high, large). Similarly, the "-" is called the low level. The treatments are symbolized by combinations of lower case letters corresponding to the factors. If a factor level is high, its lower case letter appears in the treatment symbol; if it is low, it does not. The only exception is the treatment for which all factor levels are low. This is given the special symbol "(1)".

TABLE I

A 2^3 Full Factorial Design

Observation	Factor Levels			Treatment
	A	B	C	
1	-	-	-	(1)
2	+	-	-	a
3	-	+	-	b
4	+	+	-	ab
5	-	-	+	c
6	+	-	+	ac
7	-	+	+	bc
8	+	+	+	abc

As shown in the table, the full factorial design incorporates all possible combinations of factor levels. This offers two principal advantages to the researcher. First, it simplifies the calculation of the main effects and interactions. Although the details of those computations are beyond the scope of this report, it can be shown that a full factorial design is the most efficient means of obtaining the main effects and interactions in terms of observations required (Davies, 1956:252-3). Second, it preserves the orthogonality of the factors. As mentioned in the discussion of policy-capturing, regression analysis of orthogonal factors lends itself quite easily to meaningful interpretation. Thus, a full factorial design is usually the preferred approach.

Unfortunately, there is one serious drawback to the full factorial design—the exponential relationship between the number of factors and the

number of treatments. A 2^4 design requires only 16 treatments. However, after doubling the factors from 4 to 8, the treatments mushroom to 256 (2^8). In a policy-capturing setting, this would mean obtaining 256 separate responses from every subject—not a pleasant prospect for either subject or researcher.

The alternative is to observe only a portion of the possible treatments while retaining as much information as possible. This can be accomplished through the use of fractional factorial designs, sometimes called fractional replicates (Davies, 1956:Ch 10). The process for deriving a half replicate of a 2^3 design can be illustrated with Table II.

The first four columns of Table II represent a full 2^2 design consisting of four treatments. In addition, the column labeled AB denotes the interaction effect of the factors A and B. For each treatment, the sign in the AB column results from multiplying the signs of the factors.

Assume now that A and B do not interact significantly. Then the effect of AB is essentially zero. A third factor, C, may now be introduced and "equated" to AB; that is, C will take on the same levels as indicated for AB. Provided that C does not interact with A or B, any changes in the outcomes must be attributed to the action of C. The final column of Table II shows the treatment combinations corresponding to this new fractional design. Comparison with Table I will verify that it is in fact half of the full 2^3 design.

Instead of equating C to AB, suppose it had been equated to -AB. That is, in each treatment the level of C would have been opposite that shown for AB. In that case, the other half of the 2^3 design would have

TABLE II

A Half-Replicate 2^3 Design

Observation	Treatment	A	B	AB	New Treatment (C = AB)
1	(1)	-	-	+	c
2	a	+	-	-	a
3	b	-	+	-	b
4	ab	+	+	+	abc

been obtained. Thus, the two treatment sets, termed blocks, for a half-replicate 2^3 design are

Block 1 (C = AB): a, b, c, abc

Block 2 (C = -AB): (1), ab, bc, ac

By convention, the block containing the (1) treatment is called the principal block. Here, Block 2 is the principal block.

The process of fractional replication enables a researcher to analyze a small block of data and obtain almost as much information as from a full design. In the foregoing example, the main effects of three factors can be calculated from four treatments instead of eight. When more factors are involved, similar fractional designs can be developed to accommodate them. This may include blocks that are a fourth, an eighth, a sixteenth, or a smaller fraction of a full design.

Despite its obvious advantages, fractional replication is not without its drawbacks. One is the problem of selecting how small a fractional design is desirable. Generally, it is best to equate additional factors

to the highest order interactions possible since they are least likely to be appreciable. However, small fractional designs may force the use of low order (two- or three-factor) interactions, which may not be insignificant. Thus, the researcher must balance that possibility against the economies of a smaller design.

A second problem is deciding which treatments should comprise the experimental block. Davies (1956:Ch 10) discusses a manual technique similar to the one used in deriving Table II. That technique becomes rather cumbersome for large numbers of factors. Fortunately, entire series of fractional factorial designs have been tabulated in reference works (e.g., National Bureau of Standards, 1957). These typically list the principal block for each design; other blocks may be generated by the method discussed by Davies.

Once a fractional factorial design has been selected, it can be employed in a policy capturing study just as readily as a full factorial design. This is so because the block designs preserve the orthogonality of the factors. (This fact may be verified directly from Table II.) Then, as long as interaction effects are known or can be assumed to be negligible, the regression model will produce the same weights it would have with the full design. The considerable savings produced by fractional replication will become evident during the discussion of the decision-making exercise employed in this study.

Data Collection

The purpose of this study was to determine whether the information processing behavior predicted by the Schroder-Driver-Streufert model could be observed in real decision makers. To accomplish this, it was necessary

to create an artificial decision-making environment that could be modeled through the policy capturing methodology. This was done by means of a decision-making exercise.

The key to the exercise was the kind of decision it asked the subjects to make. Since the objective was to measure information processing capabilities, it was necessary to minimize any tendency to deliberately ignore some data, to preselect a particular decision policy, or to give random responses. Therefore, the decision had to be a type that required at least an attempt to consider all the available information. Also, it had to be realistic, yet not dependent on extensive specialized knowledge or training. Finally, it had to be one where the choices were not obvious or trivial. These obstacles were not easy to overcome.

The decision finally settled upon was suggested by unpublished research conducted by Lieutenant Colonel William C. Letzkus, Assistant Professor of Financial Management in the Systems Management Department, School of Engineering, AFIT. Periodically, Colonel Letzkus has asked his students to rank a series of national problems in order of importance as they perceived them. Over time, the average rankings have been relatively stable, although individual rankings displayed considerable variance.

For the exercise, the following problem areas from Colonel Letzkus' work were selected: pollution control, illegal drug use, transportation, education, unemployment, poverty, health, and housing. They were chosen from the midrange of the average rankings. This was done in order to avoid the influence of a new problems consistently rated as highly important (e.g., energy shortage) and others rated very low (integration). Otherwise, the subjects might have been led to automatically focus on or ignore those problems without attempting to "process" the full range of information available.

To test the Schroder-Driver-Streufert model, it was necessary to estimate the amount of input at which maximum information processing would occur. That input level would be expected to produce higher information use than lower or higher levels. Other research, particularly Miller (1956), has suggested that five to seven factors were the optimal number for decision makers. Therefore, in this study it was decided to look at three levels of information input: six factors, Miller's mid-range value; a lower limit of four; and an upper limit of eight.

The decision-making exercise was constructed along the following lines. (See Appendix A for examples.) To introduce the eight problem areas, the subjects were asked to specify the priority levels they believed the federal government should employ in dealing with them, on a scale of one to nine. This step helped to insure that the subjects were not predisposed to ignore one or more of the problems, as indicated by a low priority rating. Next, they were given three factorial designs, one full and two fractional, of different numbers of problems. These designs formed the basis for the policy-capturing analyses needed to model their information processing behavior. At the end of each design, the subjects were asked to describe the weights they had given to each problem area in assessing the strategies. They did this by distributing 100 points among the problems in proportion to their perceived importance. This introduced a second check to determine whether certain problems had been ignored deliberately.

For each design, the treatments were termed strategies. Each problem area (factor) included in the designs was assigned a priority level of either HIGH or LOW. The strategies reflected the hypothetical distribution of funds, manpower, and other resources that the federal government might

allocate toward each problem area—more to HIGH priority problems and less to LOW priority ones. The subjects indicated their agreement with the strategies on a nine-point scale ranging from "Totally Disagree" (1) to "Totally Agree" (9).

The problem areas chosen for the designs were randomly selected from the eight available. The order of presentation of the problems was randomized between designs; however, within each design the order was fixed. The first set of strategies constituted a full factorial 2^4 design (16 strategies). The problem areas included were housing, illegal drug use, unemployment, and pollution control. The second set was a half-replicate 2^6 design (32 strategies) taken from the National Bureau of Standards reference (1957:6). This covered the factors of poverty, health, education, unemployment, transportation, and illegal drug use. The final set was a one-eighth replicate 2^8 design (32 strategies), also from the National Bureau of Standards work (1957:31). It of course incorporated all eight problem areas.

The exercises were administered to 70 graduate students at the AFIT School of Engineering and School of Systems and Logistics. The students were randomly selected from enrollment rosters. The exercises, along with explanatory cover letters, were distributed to individual student mail boxes in each school. Upon completion, the exercises were returned to collection boxes in the mail rooms. Follow-up notices were sent out approximately five weeks after the original distribution date requesting those who had not yet returned the exercises to do so as soon as possible.

As each exercise was returned, it was given a two-digit identification number for accounting purposes. The exercise responses were coded onto standard IBM-type computer cards. For details of the card formats, see Appendix B.

Data Analysis

As part of the policy capturing methodology, the decisions of each individual were subjected to multiple regression analysis by means of the SPSS REGRESSION program (Nie, et al, 1975:320-367; Cohen, et al, 1976). This required some restructuring of the data records. The responses of subjects A, B, C, and so on were initially recorded horizontally (row by row) on physically separate cards, as follows:

$$\begin{array}{cccccc} a_1 & a_2 & a_3 & a_4 & \cdots & a_n \\ b_1 & b_2 & b_3 & b_4 & \cdots & b_n \\ c_1 & c_2 & c_3 & c_4 & \cdots & c_n \\ \vdots & \vdots & \vdots & \vdots & & \vdots \end{array}$$

However, the REGRESSION program required that they be arranged vertically (column by column):

$$\begin{array}{cccc} a_1 & b_1 & c_1 & \cdots \\ a_2 & b_2 & c_2 & \cdots \\ a_3 & b_3 & c_3 & \cdots \\ a_4 & b_4 & c_4 & \cdots \\ \vdots & \vdots & \vdots & \\ a_n & b_n & c_n & \cdots \end{array}$$

In this format, each row corresponded to a particular treatment of the factorial design. The factor levels associated with each treatment also had to be specified. This was accomplished with the aid of a FORTRAN

program written by the researcher. The program transposed the horizontally tabulated data into the vertical format. It then added the factor levels at the beginning of each row, coded "0" for LOW and "1" for HIGH. Thus, for a treatment (decision) where the factor levels were LOW-HIGH-HIGH-LOW, in that order, and where subject A responded "6," subject B "4," and subject C "9," the resultant data record was

0110 6 4 9

The data transposition was performed separately on the four-factor, six-factor, and eight-factor data so that each could be analyzed by itself.

The principal outputs of the REGRESSION program were the standardized regression coefficients and R^2 values describing the decision policy of each individual. It also provided two statistical quantities utilized for significance testing.

Overall F-Test. Given a regression model of the form $y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_kx_k$, the overall F-test evaluated the null hypothesis

$$H_0: \ b_1 = b_2 = \ldots = b_k = 0$$

against the alternate hypothesis

$$H_1: \ b_j \neq 0 \text{ for at least one value of } j$$

This determined whether the overall model was statistically significant at some level α . In this study, an α of 0.05 was used for the overall test. Models not significant at the 0.05 level were omitted from further analysis.

Partial F-Test. Given the same type of regression model as above, for each coefficient b_j the null hypothesis

$$H_0: \ b_j = 0$$

was tested against the alternate hypothesis

$$H_1: \; b_j \neq 0$$

assuming that all other coefficients are included in the model. This provided a means for determining whether a specific variable contributed to the model at a significance level α . An α of 0.05 was used for the partial F-test. Only those factors with regression coefficients significant at the 0.05 level or below were considered to have contributed to a subject's decisions.

Once the regression analyses were completed, the number of statistically significant variables utilized in the four-factor, six-factor, and eight-factor decisions were tabulated for each individual. These three utilization values represented the information processing behavior of each subject. The utilization values were also tabulated as a proportion of the total factors available, giving an alternative portrayal of information processing.

Individuals were grouped according to their information utilization patterns by means of the SPSS discriminant analysis program DISCRIMINANT (Nie, et al, 1975:434-467). Discriminant analysis is a technique for determining how well a set of variables can be used to distinguish two or more groups from one another. In this case, the analysis was used to separate the high information users from the low ones. The means of the utilization values were computed for both groups. Two additional statistical tests were then performed to determine whether differences in the utilization patterns were significant.

Independent Samples t-Test. Given independent random samples from two normal populations with different means μ_1 and μ_2 , the null

hypothesis

$$H_0: \mu_1 - \mu_2 = 0$$

was tested against the alternate hypothesis

$$H_1: \mu_1 - \mu_2 \neq 0$$

The exact form of the test depends on whether the population variances are known and if they are equal. The independent samples t-test was applied to the mean utilization values of the two groups to determine if the respective decision behaviors differed statistically.

Paired Samples t-Test. This test was similar to the independent samples test, with identical null and alternate hypotheses. However, this test assumed that the two samples were correlated. It measured the statistical difference of mean utilization values within a given group to determine whether increases or decreases in utilization were actual or random.

Both of the above t-tests were performed using the T-TEST procedure of SPSS (Nie, et al, 1975:267-275).

A final analysis was performed using the grade point average (GPA) and aptitude test scores reported by the subjects. These were subjected to an independent samples t-test to determine whether the mean values differed between the groups. This measured the degree to which information processing ability was correlated to GPA and test score.

Summary

The hypotheses of the Schroder-Driver-Streufert model were tested in a policy capturing exercise. A series of decisions were analyzed by multiple regression to determine how many factors a subject was able to process effectively. By using fractional factorial designs, a decision-making

exercise was developed that permitted an efficient analysis with a minimum number of required responses. The exercise, distributed to 70 AFIT students, was based on rating a series of hypothetical priorities for dealing with certain national problem areas. The data analysis was performed with several SPSS programs, including REGRESSION, DISCRIMINANT, and T-TEST. These programs were used to model individual decision patterns and to test for significant differences in those patterns.

IV. RESEARCH RESULTS

Exercise Response

Of the 70 decision-making exercises originally sent out, 39 were completed and returned for a response rate of 55.7 percent. School of Engineering students returned 31, or 62 percent, of the 50 exercises distributed to them. Eight out of 20 (40 percent) of the School of Systems and Logistics students returned their exercises.

As was mentioned in Chapter III, one of the concerns in selecting the specific national problem areas for the exercise was that the subjects as a group might place extremely high or low values on certain problem areas on an *a priori* basis. Consequently, some inputs would have been filtered out because of subject bias rather than information processing limitations. As a check, the subjects were asked to indicate the priority they believed each problem area deserved before they completed the actual decision-making portion of the exercise. Each problem area was assessed on a nine-point scale ranging from "low priority" to "highest possible priority." Thus, each problem area had an associated distribution of priority assessments. Histograms of these distributions appear in Appendix C; they were produced by the SPSS program FREQUENCIES (Nie, *et al*, 1975:194-202).

Table III summarizes the key characteristics of the priority distributions. All but the last two columns are self-explanatory. The *frequency of extreme assessments*, f_e, is the percentage of responses that were one (minimum priority) or nine (maximum priority). The *frequency of moderate assessments*, f_m, is the percentage of responses giving four, five, or six as the priority level.

TABLE III

Pre-Exercise Priority Assessments

Problem Area	Mean Priority Assessment	Standard Deviation	Frequency of Extreme Assessments	Frequency of Moderate Assessments
Housing	4.9	1.6	2.6	69.2
Health	6.2	1.7	10.3	48.7
Unemployment	6.2	1.5	0.0	51.3
Education	6.5	1.9	15.4	38.5
Illegal Drug Use	5.0	2.4	10.3	30.8
Poverty	5.2	1.7	2.6	61.5
Transportation	5.7	2.0	7.7	46.1
Pollution Control	6.7	1.8	10.3	33.3

Table III shows that the mean priority assessments were all near or just above the middle of the scale, indicating that opinions did not tend to cluster substantially at either the high or low end. More importantly, the f_e column shows that a relatively small proportion of the responses were for the extreme values of "1" or "9." In every case, the frequency of moderate responses was much greater. Even for education, which had the largest f_e value, f_m was two and one-half times larger (38.5 percent compared to 15.4 percent). Consequently, it seemed reasonable to assume that, as a group, the subjects were not excessively biased for or against any of the problem areas.

After each set of decisions, the subjects were asked to distribute 100 points among the problem areas in proportion to their importance in the decision process. This was intended to detect group bias as evidenced

TABLE IV

Extreme Response Frequencies for
Post-Exercise Factor Weightings

Problem Area	Decision Set A f_e	Decision Set B f_e	Decision Set C f_e
Housing	2.6	-	23.1
Illegal Drug Use	10.3	25.6	48.7
Unemployment	0.0	2.6	12.8
Pollution Control	2.6	-	17.9
Poverty	-	10.3	41.0
Health	-	2.6	10.3
Education	-	2.6	7.7
Transportation	-	10.3	20.5

by large proportions of extreme point values. Appendix D provides histograms of the point distributions by decision set and problem area.

Table IV summarizes the distribution of extreme responses. In this case, nearly all the interesting effects occurred at the low end of the scale. Therefore, an extreme response was taken to be a point value of five or less. In three instances, the frequency of extreme responses appeared to be unusually high. This occurred for illegal drug use (25.6 and 48.7 percent for sets B and C, respectively) and poverty (41.0 percent for set C). In each case, the frequency indicated the percentage of subjects who weighted that problem area at five or less points out of 100 in importance. In addition, housing (23.1 percent for set C) and transportation (20.5 percent for set C), although not as high as the others, tended to have a substantial cluster of responses at the low end.

These instances of very low problem area weights may suggest some conscious filtering out of those problems by the subjects during the exercise. On the other hand, they may only reflect the post-exercise insight of the subjects in recognizing their inability to integrate certain inputs into their decisions. Since most of the f_e values were relatively small (less than 20 percent), these effects were most likely minimal. Although the results of the exercise must be evaluated in light of the possible bias reflected in Table IV, it is the opinion of the researcher that the effects noted did not significantly distort the outcome of the exercise.

Individual Regression Models

For each of the 39 respondents, individual regression models were derived for their four-factor, six-factor, and eight-factor decision sets. From the partial F-test described in Chapter III, the number of factors contributing significantly (at a 0.05 level) to the models was determined. By observing how the number of significant factors changed between decision sets, it was hoped that confirmation of the Schroder-Driver-Streufert information processing model would be obtained.

Of the 39 subjects, 5 failed the overall F-test for one or more of the decision sets. That is, the regression coefficients were not significantly different from zero at the 0.05 level. For the remaining 34 subjects, 3 different information utilizations were obtained, 1 from each decision set. The possible relationships between the utilization levels are illustrated in Figure 6. For example, in a Type 3 relationship, the subject used more information in the six-factor decision set than in either of the others. In contrast, a Type 6 subject used the same amount of information in the four- and six-factor sets but less in the final set.

Type	Relationships*	Graph	Number	Percentage
1	a < b < c		10	29.4
2	a < b = c		5	14.7
3	a < b > c		7	20.6
4	a = b < c		3	8.8
5	a = b = c		2	5.9
6	a = b > c		2	5.9
7	a > b < c		2	5.9
8	a > b = c		1	2.9
9	a > b > c		2	5.9
			34	100.0

* a - amount of information utilized in four-factor decision set

b - amount of information utilized in six-factor decision set

c - amount of information utilized in eight-factor decision set

Figure 6. Information Utilization Patterns

Under the interpretation suggested by the Schroder-Driver-Streufert theory, Type 3 behavior would indicate that the subject experienced information overload when the input rose above six factors. Type 3 behavior provides the strongest support for the information processing model under study. However, Types 2, 6, 8, and 9 also show evidence of decreasing information use with increasing availability. They do not display the classic inverted-U shape predicted by Schroder, et al; however, the restricted range of the experiment may account for that. Therefore, those types also lend at least partial support to the theory. Types 1 and 4 indicate subjects for whom information overload has not occurred, although presumably it could occur at some higher input level not tested in this experiment. A Type 5 (constant) response is an indeterminate case, while Type 7 (trough-shaped) completely contradicts theoretical predictions. More will be said about these last two later in this chapter.

The last two columns of Figure 6 list the number and percentage of subjects that displayed each information utilization type. Out of 34 subjects, 10 (29.4 percent) showed Type 1 behavior, consistently increasing their information use. Seven (20.6 percent) displayed Type 3 (inverted-U) patterns characteristic of the Schroder-Driver-Streufert model. Patterns reflecting the onset of information overload (Types 2, 3, 6, 8, and 9) were associated with 17 of the subjects, or half of the sample. Thirteen of the subjects (38.2 percent) showed no evidence of overload, as represented by Types 1 and 4. The decision patterns of the 4 remaining subjects were either indeterminate (Type 5) or contradictory to the theory (Type 7).

Differences in Information Utilization Patterns

The actual amount of information utilized varied widely from one individual to another. Figures 7 through 10 present the mean utilization patterns for various subject groups. In each figure, the upper graph plots the mean number of factors contributing significantly to the decisions (based upon the regression models) versus the number available in each decision set. The lower graph shows the mean proportion of available information actually used, calculated by dividing the number of significant factors by the number available. In effect, this shows how well an individual's information processing capabilities are keeping pace with rising input. In both graphs, the region indicated above and below each plotted point ranges between plus and minus one standard deviation from the mean.

Seven of the 34 subjects displayed the Type 3 pattern most strongly supporting the theory (Figure 7). The mean number of significant decision factors for this group was 2.4 for the four-factor set, 4.6 for the six-factor set, and 2.9 for the eight-factor set. Paired samples t-tests of these values revealed that the means of the first two sets were significantly different at less than the 0.001 level; those for the last two sets differed at the 0.003 level. Therefore, it was concluded that there was a true rise and subsequent decline of information utilization by the subjects in this group.

The proportional utilization graph showed the onset of information overload even more dramatically. The mean values for the three decision sets were 0.61, 0.76, and 0.36, respectively. Thus, the average subject used about three-fourths of the available information when six factors were presented, but only about one-third when eight factors were offered.

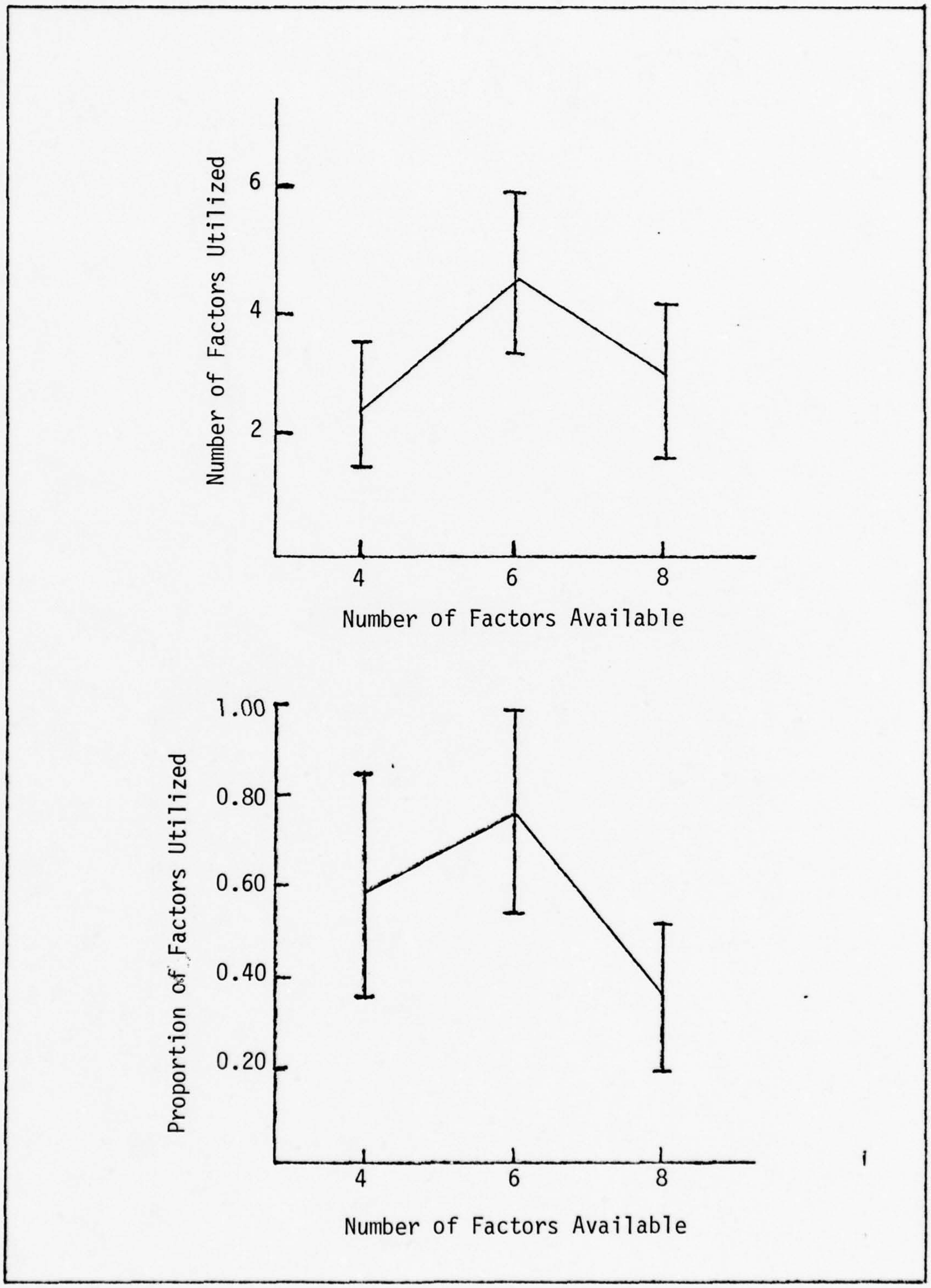


Figure 7. Type 3 Group

Taken together, the two graphs in Figure 7 demonstrate that the decision-making behavior of this subgroup is consistent with that predicted by the Schroder-Driver-Streufert model.

Ten of the 34 subjects, the largest subgroup, exhibited Type 1 decision patterns, wherein information utilization consistently increased (Figure 8). The mean utilization values were 2.4 for the four-factor decision set, 4.2 for the six-factor set, and 6.2 for the eight-factor set. The differences between these means were significant at a level of less than 0.001, as determined by paired samples t-tests. The mean proportion of information utilized also increased from 0.60 to 0.70 to 0.78. For this subgroup, information overload did not occur; in fact, information processing capability appeared to be increasing over the range of the experiment.

The remaining half of the subjects demonstrated decision patterns other than the two simple ones described above. Although it is possible that the information processing qualities of those individuals did not conform to the theoretical predictions, those differences may be attributed more reasonably to the limitations of the experimental design. Recall that the hypothetical U-curves were being sampled at only three points. Also, the sampling points were separated by two units rather than one. Consequently, there was no way to tell what results would have been obtained if the subjects had been given five or seven factors to consider. Thus, where utilization appeared to be unchanged between two points, there actually might have been an undetected increase at the intermediate value. This raised the possibility that the remaining subjects could be classified into one of the two preceding groups based on similarities in their patterns.

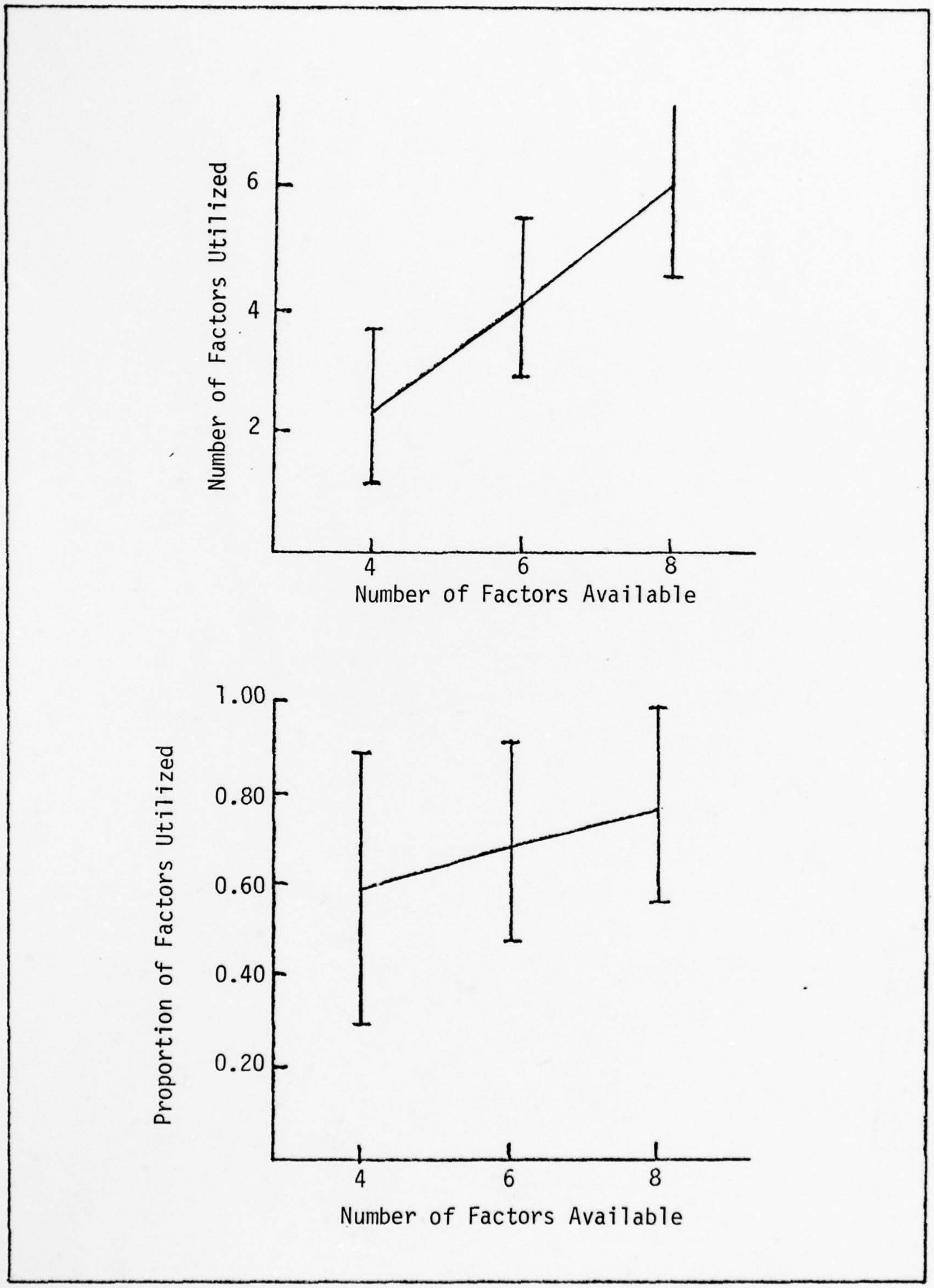


Figure 8. Type 1 Group

This possibility was investigated through discriminant analysis. The subjects with Type 1 (no overload) patterns formed one group; those with Type 3 (overload) patterns formed the second group. The SPSS DISCRIMINANT program analyzed the two groups in terms of the factor utilizations in each decision set. (The analysis was conducted using both raw factor numbers and proportions, with identical results.) The program derived a discriminant function from the two known groups, then classified the remaining subjects according to their scores from that function. It also assigned a conditional probability of group membership to each subject—the probability that the subject belonged to the assigned group, given the discriminant function score.

The discriminant analysis conclusively separated the subjects into the two predefined groups. The mean probability of group membership across all 34 subjects was 0.983; the lowest probability for any subject was 0.794. The 17 subjects with known group membership were all classified without error. Of the remaining 17, 12 were assigned to the Type 3 (overload) group and 5 to the Type 1 (no overload) group. Therefore, under this classification scheme 15 subjects (46 percent) did not experience information overload and 19 subjects (54 percent) did.

The subjects newly classified as "no overload" types all shared one quality: information utilization increased between the six-factor and eight-factor decision sets. Thus, the "no overload" group contained Type 1, 4, and 7 patterns. All the others were considered "overload" types. The effects of including these subjects can be observed in Figures 9 and 10.

Figure 9 shows the usual graphs of the mean utilization values for the new "overload" group. The dashed lines represent the values that appeared in Figure 7 for the Type 3 subjects alone. The peak of the upper graph was less pronounced than before; the three means were 2.7, 3.6, and

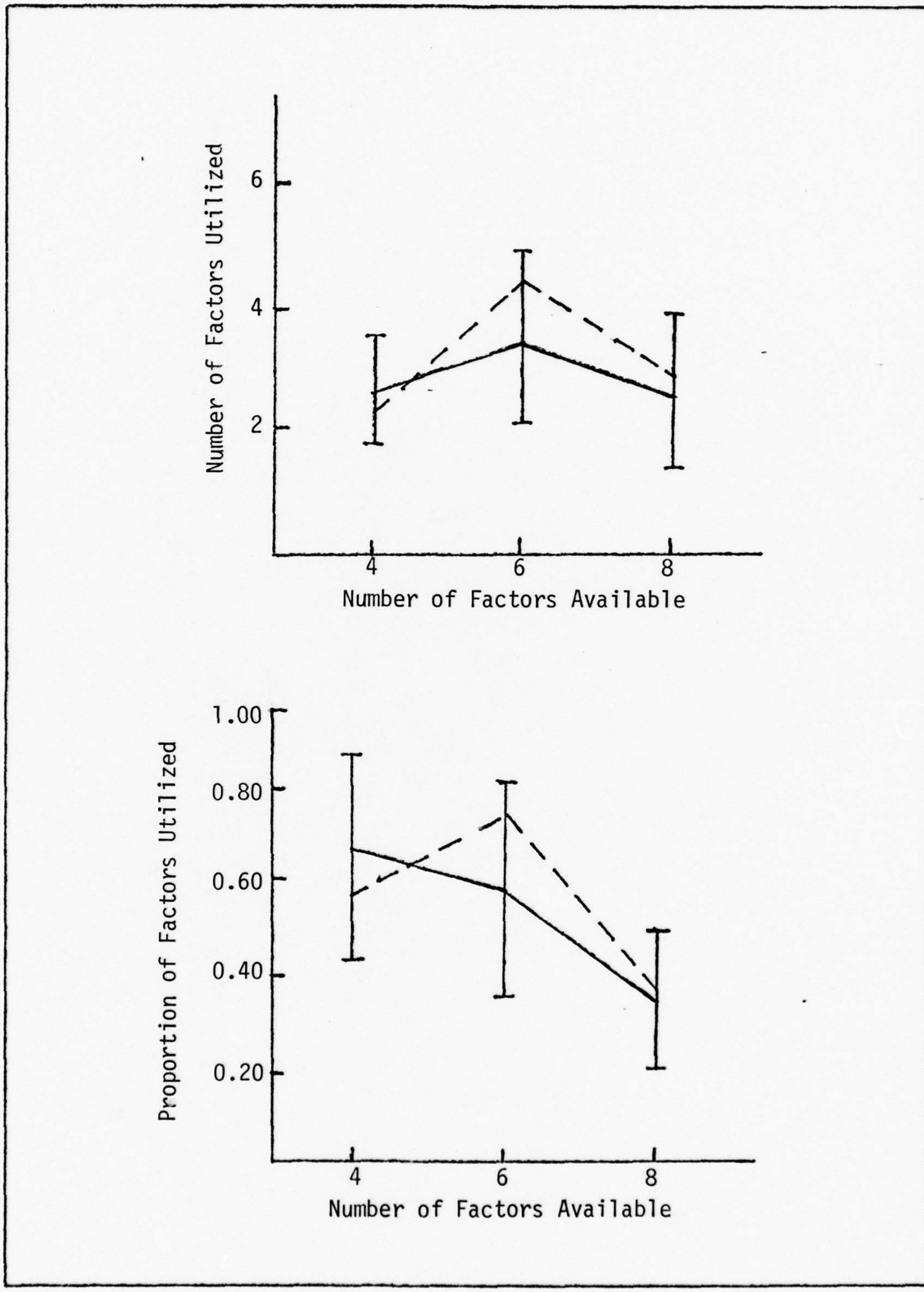


Figure 9. Composite "Overload" Group

2.7, respectively. However, the difference between the first two was still significant at the 0.011 level (paired samples t-test). The second two also differed statistically at the 0.001 level. This indicated that the shape of this composite graph, and particularly the drop in utilization between the six-factor and eight-factor sets, was statistically "real."

The lower, proportional graph lost its former peak completely. The mean values for this graph were 0.68, 0.61, and 0.34. However, the 0.07 difference for the first two was not significant ($p = 0.202$), while the second difference of 0.27 was ($p < 0.001$). Thus, the composite group retained the substantial decrease in proportional information use noted in the original group.

Owing to the small number of additional members, the composite "no overload" group was little changed from the original Type 1 patterns (Figure 10). The mean utilization values for the upper graph were 2.7, 3.8, and 6.2, all of which were significantly different at the 0.008 level or less (paired samples t-test). For the lower graph, the mean proportions were 0.68, 0.63, and 0.78. However, the 0.05 difference in the first two was not significant ($p = 0.503$), although the difference in the last two was ($p = 0.005$). This would seem to indicate a moderate increase in information utilization—less pronounced than for the pure Type 1 group but still observable.

None of the foregoing tests addressed the issue of determining to what degree the "overload" utilization patterns differed from the "no overload" patterns. This was done with the independent samples t-test, and the results appear in Table V. (Although the tabled values are based on the numbers of factors utilized, the same results were obtained from the proportional figures.) Whether comparing just the Type 1 and

Type 3 means or the means for the composite groups, the first two values were essentially equal. The only significant distinction between the utilization curves was in the eight-factor decision set. This suggests that information processing capabilities were relatively uniform for all individuals until information overload occurred.

It is interesting to note that the classification into "overload" and "no overload" groups based upon the discriminant analysis agreed almost exactly with the a priori groupings discussed earlier in this chapter. For example, it was stated that Type 1 and 4 patterns did not reflect information overload. The discriminant analysis added only one other pattern—Type 7. Similarly, the "overload" groups differed only by the addition of Type 2 by the discriminant analysis. The close correspondence of these groupings lends some empirical weight to the a priori assumptions.

The appearance of Type 2 and 7 patterns posed some serious problems of interpretation. It was not immediately clear how such behaviors could arise if the Schroder-Driver-Streufert model were true. An examination of the actual exercise forms revealed no notes, markings, or other hints to explain how the individuals had structured their decision-making. Still, there were some plausible (if not provable) explanations for these phenomena that are consistent with the theory.

Consider first the Type 2 (constant level of utilization) pattern. One possibility is that the true point of optimum information processing occurred at an input value not measured, either outside the experimental range or between the values that were included. However, the flatness of the Type 2 pattern casts doubt on that interpretation. In such a situation, information overload would have had to occur rapidly; the graph

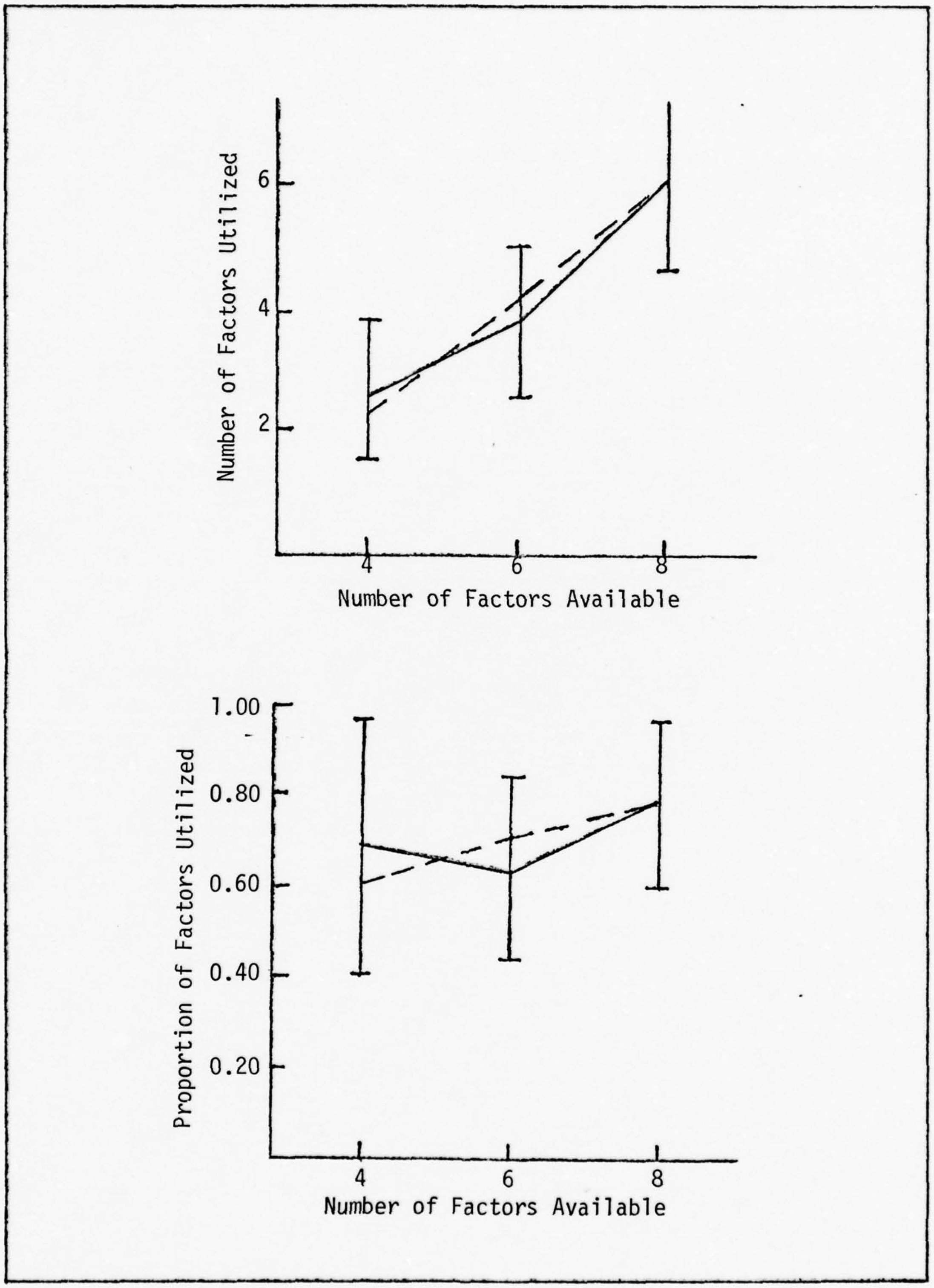


Figure 10. Composite "No Overload" Group

TABLE V

Between-Group Comparisons of Utilization Patterns

Group	A Mean (Std Dev)	B Mean (Std Dev)	C Mean (Std Dev)
Type 1 Only (n = 10)	2.40 (1.17)	4.20 (1.32)	6.20 (1.62)
Type 3 Only (n = 7)	2.43 (0.98)	4.57 (1.27)	2.86 (1.22)
Difference	−0.03	−0.37	3.34
Significance	0.957	0.569	0.000
Composite "No Overload" (n = 15)	2.73 (1.10)	3.80 (1.21)	6.20 (1.47)
Composite "Overload" (n = 19)	2.74 (0.87)	3.63 (1.38)	2.68 (1.34)
Difference	−0.01	0.17	3.52
Significance	0.992	0.707	0.000

A - Four-factor decision set

B - Six-factor decision set

C - Eight-factor decision set

would have possessed a spike at that point rather than the broader peak more characteristic of the Schroder-Driver-Streufert model.

Perhaps a more reasonable interpretation is simply that the subject did not take the exercise seriously. The decisions were, after all, remote from the everyday experiences of the typical student, and there were 80 decisions to make. It is quite conceivable that a few subjects consciously or unconsciously selected a comfortable information processing level and maintained it throughout the exercise. At the very least, this explanation seems to possess more intuitive appeal than the previous one.

The Type 7 pattern, consisting of a decrease and subsequent rise in information utilization, probably can be most easily and reasonably explained by assuming a change in the information processing structure prior to the rise in utilization. Presumably, the subject experienced information overload early. Upon reaching the minimum point and facing a series of eight-factor decisions, the subject might have decided to change decision models. Rather than relying on the internal functioning of the brain to integrate the data, the individual may have set up an explicit model with predetermined factor weights and a scoring scheme to "assist" in the decision-making. In effect, the subject would trade an internal model for an external one.

The regression models of the two Type 7 subjects seem to support this interpretation. The relative weights for each factor were calculated according to Eq (3) of Chapter III and compared to the self-reported weights for the eight-factor decision set. For both subjects, the two sets of weights agreed quite closely, differing by no more than eight points. The agreement for the other two sets was much less. In addition,

the R^2 values for the eight-factor sets were 0.988 and 0.963 for the Type 7 subjects, both reflecting unusually high consistency in decision-making. In contrast, the R^2 figures for the six-factor sets were 0.455 and 0.828, indicating appreciably more variance unaccounted for by the (regression) decision model. Thus, it seems likely that the Type 7 subjects actually did experience information overload, but compensated for it by switching to an explicit external decision model.

GPA and Test Score Differences

A secondary objective of this research was to test if an individual with a given information processing pattern tended to have a higher cumulative grade point average (GPA) or aptitude test score. The independent samples t-test was used to determine whether the mean GPAs and percentile test scores for the composite "overload" and "no overload" groups were appreciably different.

Nine of the composite "overload" subjects reported their GPAs. The mean GPA was 3.46, with a standard deviation of 0.37. Eight of the composite "no overload" subjects provided GPAs. Their mean was 3.64, with a standard deviation of 0.29. The t-test found that the difference in GPAs was not significant ($p = 0.277$). Therefore, GPA did not appear to correlate substantially with information processing capability.

Eight of the "overload" group reported their most recent percentile scores on standardized aptitute tests (e.g., GRE, GMAT, SAT). The mean score was 85.6, with a standard deviation of 10.8. The "no overload" group reported ten scores, averaging 89.4 with a standard deviation of 11.3. Again, the t-test showed these values not to be significantly different ($p = 0.481$). Therefore, a connection between scholastic aptitude, as measured by standardized tests, and information processing capabilities could not be supported.

Interviews with Type 1 and Type 3 Subjects

Thus far, distinctions between Type 1 and Type 3, or "overload" and "no overload," behaviors have centered strictly on the amount of information used in making decisions. No attempt has been made to explore possible differences in how those decisions were made. Nevertheless, it is conceivable that Type 1 subjects outperformed Type 3 individuals, not because they were inherently more capable, but because they used a more concrete method. Suppose, for example, that one subject started with a basic agreement rating of "5" for every strategy, then added or subtracted points depending on whether the stated priorities matched the subject's own. Similar "scorekeeping" methods could enable individuals to achieve much higher information utilization than those who dealt with the problem on a more intuitive basis.

In an attempt to discover whether "scorekeeping" played a role in this experiment, three Type 1 and three Type 3 subjects were interviewed informally and asked to explain how they made their decisions on the exercise. Of the Type 1 subjects, two indicated that they had definitely set up "scorekeeping" processes to help them assimilate the data; one specifically mentioned using such an approach after looking ahead in the exercise and seeing how complicated the decisions would be. The third Type 1 subject was less definite about the method used, but also seemed to have planned ahead for each decision set. By contrast, only one of the Type 3 subjects admitted to using "bookkeeping" (subject's term), and then only to a limited extent toward the end of the exercise.

These informal interviews, although not conclusive, certainly suggest that a substantial portion of Type 1 behavior might have resulted from the use of predetermined decision rules. Thus, the occurrence of information

overload may have been artificially masked in those subjects. In reality, their information processing capabilities may have been no better than those of the Type 3 individuals.

V. SUMMARY AND CONCLUSIONS

Summary of the Research

The research documented herein examined decision-making in the context of human information processing. The Schroder-Driver-Streufert model of human information processing served as the foundation of the study. This model predicted that the ability to use information reached a maximum at some level of information input and decreased at higher levels. Consequently, the model provided a practical framework for investigating information overload.

Objectives. The primary objective of the research was to test two hypotheses proposed by the Schroder-Driver-Streufert model. The first predicted that, as the amount of available information increased, a point would be reached beyond which the amount used to arrive at a decision would decrease (i.e., information overload would occur). The second stated that some individuals consistently used more of the available information to make decisions than others did, for all levels of input.

Two secondary objectives were also pursued. One was to determine whether individual information processing capabilities were correlated to academic ability or achievement, as measured by standardized aptitude tests and cumulative grade point averages, respectively. The other was to test the appropriateness of policy capturing as a methodology for this type of decision-making study.

Methodology. To accomplish the research objectives, it was necessary to measure the amount of information used by an individual to reach a

decision and compare it to the amount of information made available. This was done by means of a three-part policy capturing exercise. Each subject was asked to make a series of decisions concerning national priorities in eight different problem areas. The first set of decisions included four problem areas; the second contained six; and the third, all eight. Regression models for the three sets of decisions were then developed and statistically tested to determine how many of the stated problem areas significantly affected the decisions. The resulting numbers corresponded to the amount of information used in the Schroder-Driver-Streufert model.

The patterns of information utilization obtained from the policy capturing exercise were subjected to discriminant analysis and to t-tests of the mean values (both paired and independent samples) in order to discover if the hypothesized information processing behaviors had occurred. The t-tests were also used to determine whether the utilization patterns were related to grade point averages or aptitude test scores.

Review of Significant Findings

The significant findings of this research were as follows:

1. The policy-capturing methodology provided statistically significant regression models of all three decision sets for 34 (87 percent) of the 39 subjects.

2. Considerable variation in information utilization patterns was noted. Approximately 29 percent of the subjects continued to process more information as more became available. About 21 percent experienced a drop in the amount of information processed when input rose above six factors. The remaining 50 percent demonstrated the seven other modes of behavior possible under this experimental design.

3. A discriminant analysis of the information utilization patterns showed that all subjects could be conclusively classified into one of the two groups: one in which information utilization consistently increased ("no overload" group), and one in which utilization decreased for an input of more than six factors ("overload" group).

4. The amount of information processed by the "overload" and "no overload" groups did not differ significantly at either the four-factor or six-factor input levels. Only after information overload occurred in the first group was a statistically meaningful separation evident.

5. The information processing abilities of individuals had no apparent correlation with either their cumulative AFIT grade point averages or their academic aptitude test scores.

Conclusions and Implications

This research was undertaken to test two hypotheses related to the Schroder-Driver-Streufert information processing model. Two secondary objectives were also pursued: an evaluation of policy capturing as a tool for studying human information processing, and a determination of the relationship between information processing capability, grade point average, and aptitude test scores. The conclusions and implications drawn from the research results relevant to each of these objectives are presented in the following paragraphs.

Hypothesis 1. "As the amount of available information increases, a point is reached beyond which the individual decreases the amount of information used to reach a decision."

Conclusion: The research supported this hypothesis for at least part of the sample. Fifty-six percent of the subjects with well-defined

decision models did experience a decrease in information utilization. The other 44 percent did not demonstrate the expected behavior within the range of the experiment. Thus, it could not be determined whether the hypothesis applied to this group.

Implications: A surprisingly large number of individuals continued to increase their use of information even after being given eight factors to consider. This suggested that the range of individual information processing capabilities is somewhat broader than originally envisioned and that future experiments might profit by expanding beyond eight factors.

Hypothesis 2. "Some individuals consistently incorporate more of the available data into their decision making than do others."

Conclusion: The research did not support this hypothesis. To do so, the data would have had to show that the amount of information used by the "no overload" group was always greater than that for the "overload" group. This was true only for the eight-factor decision set in this exercise. Therefore, it was concluded that essentially no difference in information processing existed between the groups prior to the onset of information overload.

Implications: The lack of support for this hypothesis indicated a deficiency in either the hypothesis itself or in the manner in which it was tested. Further tests, perhaps under different experimental designs, may be necessary to clearly determine the correct explanation.

GPAs and Test Scores. Conclusion: For this sample (AFIT students), neither GPAs nor test scores were associated to any great degree with information processing ability. Therefore, it is not feasible to predict information processing behavior from a GPA or test score, and vice versa.

Implications: A sample consisting of AFIT students is certainly biased in its distribution of GPAs and test scores because of admission and academic standards. A more diverse sample from a wider range of disciplines and student types probably would offer a more meaningful test of the relationship.

Policy Capturing. Conclusion: The application of policy capturing to the study of human information processing was found to be both practical and fruitful. Coupled with the analytic power of SPSS, policy capturing offered a convenient method for the investigation of decision-making behavior. The use of fractional factorial designs greatly reduced the number of decisions required for the analysis, from over 300 down to 80.

Implications. If policy capturing continues to serve as a methodology for studying human information processing, it is likely that fractional factorial designs will figure prominently in the process. Without them, research instruments would grow rapidly in size and complexity as higher levels of input were included, soon becoming unwieldly.

Human information processing is a field rich in possibilities for investigation. This research has barely scratched the surface. Yet, by introducing the policy capturing technique in this context, it is hoped that others may be encouraged to examine the Schroder-Driver-Streufert framework and to further develop our understanding of human decision-making.

Bibliography

Ackoff, R. L. "Management Misinformation System." Management Science, 14: B147-B156 (December 1967).

Beach, Lee Roy. "Multiple Regression as a Model for Human Information Utilization." Organizational Behavior and Human Performance, 2: 276-289 (1967).

Brown, T. R. "A Comparison of Judgmental Policy Equations Obtained From Human Judges Under Natural and Contrived Conditions." Mathematical Biosciences, 15: 205-230 (1972).

Brunswik, Egon. The Conceptual Framework of Psychology. Chicago: The University of Chicago Press, 1952.

Cohen, Claude, Bruce Foster, Wayne Helm, and James Tuccy. SPSS REGRESSION Reference, Manual Number 414. Evanston, Illinois: Northwestern University, June 1976.

Davies, Owen L. The Design and Analysis of Industrial Experiments (Second edition). London: Oliver and Boyd, 1956.

Dermer, Jerry D. "Cognitive Characteristics and the Perceived Importance of Information." Accounting Review, 48: 511-519 (July 1973).

Driver, Michael J. and Theodore J. Mock. "Human Information Processing, Decision Style Theory, and Accounting Information Systems." Accounting Review, 50: 490-508 (July 1975).

Driver, Michael J. and Siegfried Streufert. "Integrative Complexity: An Approach to Individuals and Groups as Information-Processing Systems." Administrative Science Quarterly, 14: 272-285 (June 1969).

Freund, John E. Mathematical Statistics (Second edition). Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1971.

Hoffman, Paul J. "The Paramorphic Representation of Clinical Judgment." Psychological Bulletin, 57: 116-131 (March 1960).

Miller, George A. "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information." Psychological Review, 63: 81-97 (March 1956).

Miller, Henry. "Environmental Complexity and Financial Reports." Accounting Review, 47: 31-37 (January 1972).

Mock, Theodore J. "Comparative Values of Information Structures." Empirical Research in Accounting: Selected Studies (supplement), Journal of Accounting Research, 7: 124-139 (1969).

Mock, Theodore J., Teviah L. Estrin, and Miklos A. Vasarhelyi. "Learning Patterns, Decision Approach, and Value of Information." Journal of Accounting Research, 10: 129-153 (Spring 1972).

National Bureau of Standards. Fractional Factorial Experimental Designs for Factors at Two Levels. Washington, D.C.: Government Printing Office, April 1957.

Nie, Horman H., C. Hadlai Hull, Jean G. Jenkins, Karin Steinbrenner, and Dale H. Bent. Statistical Package for the Social Sciences (Second edition). New York: McGraw-Hill Book Company, 1975.

Revsine, Laurence. "Data Expansion and Conceptual Structure." Accounting Review, 45: 704-711 (1970).

Schroder, Harold M., Michael J. Driver, and Siegfried Streufert. Human Information Processing. New York: Holt, Rinehart, and Winston, Inc., 1967.

Slovic, Paul and Sarah Lichtenstein. "Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgment." Organizational Behavior and Human Performance, 6: 649-744 (1971).

Streufert, Siegfried and Michael J. Driver. "Conceptual Structure, Information Load and Perceptual Complexity." Psychonomic Science, 3: 249-250 (September 1965).

Streufert, Siegfried and Harold M. Schroder. "Conceptual Structure, Environmental Complexity and Task Performance." Journal of Experimental Research in Personality, 1: 132-137 (October 1965).

Streufert, Siegfried, Peter Suedfeld, and Michael J. Driver. "Conceptual Structure, Information Search, and Information Utilization." Journal of Personality and Social Psychology, 2: 736-740 (November 1965).

APPENDIX A

Sample Student Decision-Making Exercise

STUDENT DECISION-MAKING EXERCISE

This study examines how intelligent individuals use information to arrive at certain decisions. You have been asked to participate because, as a graduate student, it is believed that you are an effective decision maker. The data collected in this study will be kept completely confidential. Your name will not appear in the final report, an AFIT master's thesis.

To compensate you for taking the time to complete this exercise, I will make available to you a confidential summary analysis of your decision-making behavior compared to that of your contemporaries. If you would like to receive this analysis (available September 1978), please complete the blocks below:

____
Grade and Name

____
Address

____
City State ZIP

USAF SCN 78-123
Expires 22 September 1978

PRIVACY ACT STATEMENT

In accordance with AFR 12-35, paragraph 30, the following information is provided as required by the Privacy Act of 1974:

a. Authority

(1) 5 U.S.C. 301, Departmental Regulations: and/or

(2) 10 U.S.C. 80-12, Secretary of the Air Force, Powers and Duties, Delegation By.

b. Principal purposes. The survey is being conducted to collect information to be used in research aimed at illuminating and providing inputs to the solution of problems of interest to the Air Force and/or DOD.

c. Routine uses. The survey data will be converted to information for use in research of management related problems. Results of the research, based on the data provided, will be included in a written Master's thesis and may also be included in published articles, reports, or texts. Distribution of the results of the research, based on the survey data, whether in written form or orally presented, will be unlimited.

d. Participation in this survey is entirely voluntary.

e. No adverse action of any kind may be taken against any individual who elects not to participate in any or all of this survey.

USAF SCN 78-123
Expires 22 September 1978

SECTION I

Personal Data

1. School: Engineering______________ Systems & Logistics_______

*2. What is your AFIT cumulative grade point average?______________

*3. What was your percentile score on the last standardized aptitude test (SAT, GRE, GMAT, etc.) you took before entering AFIT?

   (Report total or composite percentile score.)_________________

* If you cannot remember or locate this information, the researcher will extract it from your AFIT files. To enable him to do so, please complete the following. (Your name will not be associated with this data at any time during the analysis.)

____

Grade and Name

____

Class Section

____

Faculty Advisor

SECTION II

In this section, you are asked to indicate the priority level you believe the federal government should employ in dealing with eight national problem areas. The priority you assign to each problem area should reflect the amount of funds, manpower, and other resources that should be allocated by the federal government towards solving that problem area. Each problem area should be considered independently of the others; that is, two or more problem areas may be assigned equal priorities if you wish.

SECTION II

Please circle the response that best represents your opinion:

1. At the national level, the problem area of housing should receive:

   1.......2.......3.......4.......5.......6.......7.......8.......9

   Low Priority — Highest Possible Priority

2. At the national level, the problem area of health should receive:

   1.......2.......3.......4.......5.......6.......7.......8.......9

   Low Priority — Highest Possible Priority

3. At the national level, the problem area of unemployment should receive:

   1.......2.......3.......4.......5.......6.......7.......8.......9

   Low Priority — Highest Possible Priority

4. At the national level, the problem area of education should receive:

   1.......2.......3.......4.......5.......6.......7.......8.......9

   Low Priority — Highest Possible Priority

5. At the national level, the problem area of illegal drug use should receive:

   1.......2.......3.......4.......5.......6.......7.......8.......9

   Low Priority — Highest Possible Priority

6. At the national level, the problem area of poverty should receive:

   1.......2.......3.......4.......5.......6.......7.......8.......9

   Low Priority — Highest Possible Priority

7. At the national level, the problem area of <u>transportation</u> should receive:

1.......2.......3.......4.......5.......6.......7.......8.......9

Low Priority — Highest Possible Priority

8. At the national level, the problem area of <u>pollution control</u> should receive:

1.......2.......3.......4.......5.......6.......7.......8.......9

Low Priority — Highest Possible Priority

SECTION III

This section presents a number of different national strategies for dealing with the problem areas described in Section II. In each case, you will be told the priority level (HIGH or LOW) associated with each problem area included in that particular national strategy. As before, the priority indicates the amount of funds, manpower, and other resources to be allocated toward each of the problem areas addressed. Your task is to <u>use all the information provided to you</u> to decide the extent of your agreement or disagreement with each strategy.

Part A concerns national strategies aimed at four problem areas only. Part B concerns national strategies aimed at six problem areas. Part C concerns national strategies aimed at eight problem areas. You should work through the cases at a comfortable pace, without rushing through or lingering over them. BE SURE TO COMPLETE EVERY CASE. EACH CASE IS <u>DIFFERENT</u>.

NOTE: The next two pages are samples from the four-factor decision set. The formats for the six-factor and eight-factor sets were similar.

- -

STRATEGY A-1

PROBLEM AREA	PRIORITY
Housing	HIGH
Illegal Drug Use	LOW
Unemployment	LOW
Pollution Control	HIGH

Indicate your level of agreement with this strategy:

1.......2.......3.......4.......5.......6.......7.......8.......9
Totally Disagree ... Totally Agree

- -

STRATEGY A-2

PROBLEM AREA	PRIORITY
Housing	HIGH
Illegal Drug Use	HIGH
Unemployment	LOW
Pollution Control	LOW

Indicate your level of agreement with this strategy:

1.......2.......3.......4.......5.......6.......7.......8.......9
Totally Disagree ... Totally Agree

- -

Please indicate the relative importance that you believe you placed upon each of the four problem areas in Part A by distributing 100 points among these areas. The most important area should receive the most points, etc.

PROBLEM AREA	POINTS
Housing	________
Illegal Drug Use	________
Unemployment	________
Pollution Control	________
TOTAL POINTS	100

APPENDIX B

Data Card Formats

APPENDIX B

Data Card Formats

The responses from the decision-making exercise were coded onto IBM-type cards as outlined below. The data record for each subject consisted of three cards. The first contained the responses from Sections I and II of the exercise (see Appendix A) and the four-factor decision set. The second card recorded the six-factor set, and the third card the eight-factor set.

Card No.	Columns	Format	Contents
1	1-2	I2	Subject identification number
1	4	A1	Request for individual summary of results (Y = wanted summary; N = did not want summary)
1	5	A1	AFIT school attended (E = Engineering; L = Systems & Logistics)
1	7-10	F4.2	AFIT cumulative grade point average
1	11-13	I3	Percentile score on last aptitude test
1	15-22	8I1	Pre-exercise priority assessments
1	24-39	16I1	Agreement ratings for four-factor strategies
1	40-51	4I3	Post-exercise factor weightings for four-factor decision set
2	1-2	I2	Subject identification number
2	4-35	32I1	Agreement ratings for six-factor strategies
2	36-53	6I3	Post-exercise factor weightings for six-factor decision set
3	1-2	I2	Subject identification number

Card No.	Columns	Format	Contents
3	4-35	32I1	Agreement ratings for eight-factor strategies
3	36-59	8I3	Post-exercise factor weightings for eight-factor decision set

APPENDIX C

Pre-Exercise Priority Assessment Histograms

APPENDIX C

Pre-Exercise Priority Assessment Histograms

The histograms on the following pages, produced by the SPSS program FREQUENCIES, illustrate the distributions of priority assessments given to the eight national problem areas at the beginning of the exercise. The assessments ranged from one (low priority) to nine (highest possible priority). A value of zero indicates that no response was given. The actual number of subjects who gave each response is listed in parentheses to the right of the associated bar.

DRUG USE PRIORITY

```
CODE
     I
   0 ****** (      1)
     I
     I
  1. **************** (      3)
     I
     I
  2. ****** (      1)
     I
     I
  3. ***************************************** (      8)
     I
     I
  4. ************************* (      5)
     I
     I
  5. ****** (      1)
     I
     I
  6. ******************************* (      6)
     I
     I
  7. ******************************* (      6)
     I
     I
  8. ***************************************** (      8)
     I
     I
     I.........I.........I.........I.........I.........I
     0         2         4         6         8        10
     FREQUENCY
```

EDUCATION PRIORITY

```
CODE
        I
   2.   ****** (         1)
        I
        I
   3.   *********** (         2)
        I
        I
   4.   ********************* (         4)
        I
        I
   5.   ********************* (         4)
        I
        I
   6.   ************************************ (         7)
        I
        I
   7.   ***************************************** (         8)
        I
        I
   8.   ************************************ (         7)
        I
        I
   9.   ******************************* (         6)
        I
        I
        I.........I.........I.........I.........I.........I
        0         2         4         6         8        10
        FREQUENCY
```

```
        HEALTH PRIORITY

CODE
        I
   3.   **********  (       2)
        I
        I
   4.   ********************  (       4)
        I
        I
   5.   ****************************************  (       8)
        I
        I
   6.   ***********************************  (       7)
        I
        I
   7.   *********************************************  (       9)
        I
        I
   8.   *************************  (       5)
        I
        I
   9.   ********************  (       4)
        I
        I
        I.........I.........I.........I.........I.........I
        0         2         4         6         8        10
        FREQUENCY
```

```
      HOUSING PRIORITY

CODE
      I
  1.  *** (      1)
      I
      I
  2.  ****** (      2)
      I
      I
  3.  ****** (      2)
      I
      I
  4.  ************************** (     10)
      I
      I
  5.  ********************************* (     13)
      I
      I
  6.  ********** (      4)
      I
      I
  7.  ************ (      5)
      I
      I
  8.  ****** (      2)
      I
      I
      I.........I.........I.........I.........I.........I
      0         4         8        12        16        20
      FREQUENCY
```

POLLUTION PRIORITY

```
CODE
    I
 1. *** (      1)
    I
    I
 3. ******** (      3)
    I
    I
 5. ****** (      2)
    I
    I
 6. **************************** (     11)
    I
    I
 7. ************* (      5)
    I
    I
 8. ************************************ (     14)
    I
    I
 9. ******** (      3)
    I
    I
    I.........I.........I.........I.........I.........I
    0         4         8         12        16        20
    FREQUENCY
```

POVERTY PRIORITY

```
CODE
     I
  2. *********** (       2)
     I
     I
  3. ********************* (       4)
     I
     I
  4. ************************************ (       7)
     I
     I
  5. ********************************************** (       9)
     I
     I
  6. ***************************************** (       8)
     I
     I
  7. ******************************* (       6)
     I
     I
  8. *********** (       2)
     I
     I
  9. ****** (       1)
     I
     I
     I.........I.........I.........I.........I.........I
     0         2         4         6         8        10
     FREQUENCY
```

```
TRANSPORTATION PRIORITY

CODE
     I
  2. **********  (     2)
     I
     I
  3. ********************  (     4)
     I
     I
  4. *************************  (     5)
     I
     I
  5. ****************************************  (     8)
     I
     I
  6. *************************  (     5)
     I
     I
  7. ***********************************  (     7)
     I
     I
  8. *************************  (     5)
     I
     I
  9. ***************  (     3)
     I
     I
     I.........I.........I.........I.........I.........I
     0         2         4         6         8        10
     FREQUENCY
```

UNEMPLOYMENT PRIORITY

```
CODE
     I
  2. ****** (       2)
     I
     I
  4. ****** (       2)
     I
     I
  5. *************** (       5)
     I
     I
  6. ************************************ (      12)
     I
     I
  7. ****************************** (      10)
     I
     I
  8. ********************* (       7)
     I
     I
     I.........I.........I.........I.........I.........I
     0         4         8         12        16        20
     FREQUENCY
```

APPENDIX D

Post-Exercise Factor Weighting Histograms

AD-A065 912 AIR FORCE INST OF TECH WRIGHT-PATTERSON AFB OHIO SCH--ETC F/G 5/10

AN INVESTIGATION OF A HUMAN INFORMATION PROCESSING MODEL FOR DE--ETC(U)

SEP 78 D R UNGER

UNCLASSIFIED AFIT/GSM/SM/78S-23 NL

2 OF 2

AD A065912

END

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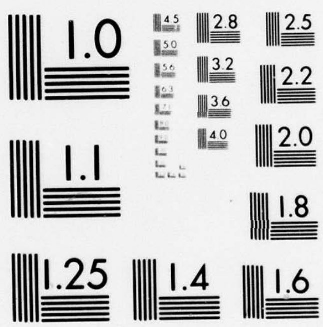
DDC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1.1
1.25
1.4
1.6
1.8
2.0
2.2
2.5
2.8
3.2
3.6
4.0
4.5
5.0
5.6
6.3

APPENDIX D

Post-Exercise Factor Weighting Histograms

At the end of each decision set, each subject was asked to distribute 100 points among the problem areas for that set in proportion to the weights they were given in reaching the decisions. The following histograms, produced by the SPSS program FREQUENCIES, depict the distribution of the weights by problem area and decision set. In each histogram, the letter A, B, or C appears after the problem area name. This indicates whether the distribution is for the four-factor, six-factor, or eight-factor decision set, respectively. Each code number down the left side of the histogram represents a range of point values:

Code	Point Value Range
1	0-5
2	6-10
3	11-15
4	16-20
5	21-25
6	26-30
7	31-35
8	36-40
9	41-45
10	46-50
11	51-55
12	56-50
13	61 or more

The number of subjects who assigned point values within a particular range is listed in parentheses to the right of the associated bar.

```
     DRUG USE-A

CODE
     I
  1. *********** (       4)
     I
     I
  2. ****************************** (       12)
     I
     I
  3. ************* (       5)
     I
     I
  4. ******************** (       8)
     I
     I
  5. **************** (       6)
     I
     I
  6. ****** (       2)
     I
     I
  7. ****** (       2)
     I
     I
     I.........I.........I.........I.........I.........I
     0         4         8        12        16        20
     FREQUENCY
```

```
         DRUG USE-8

    CODE
         I
      1. *************************  (      10)
         I
         I
      2. ***********************************  (      14)
         I
         I
      3. *****************  (       7)
         I
         I
      4. ***************  (       6)
         I
         I
      5. ***  (       1)
         I
         I
      7. ***  (       1)
         I
         I
         I.........I.........I.........I.........I.........I
         0         4         8         12        16        20
         FREQUENCY
```

```
     DRUG USE-C

CODE
     I
  1. *********************************************** (     19)
     I
     I
  2. ******************** (     8)
     I
     I
  3. ******************** (     8)
     I
     I
  4. ******** (     3)
     I
     I
  5. *** (     1)
     I
     I
     I.........I.........I.........I.........I.........I
     0         4         8         12        16        20
     FREQUENCY
```

```
EDUCATION-3

CODE
        I
  1.    *** (       1)
        I
        I
  2.    ****** (       2)
        I
        I
  3.    ******************** (       8)
        I
        I
  4.    **************************** (      11)
        I
        I
  5.    ************* (       5)
        I
        I
  6.    *********************** (       9)
        I
        I
  8.    ******** (       3)
        I
        I
        I.........I.........I.........I.........I.........I
        0         4         8        12        16        20
        FREQUENCY
```

```
      EDUCATION-C

CODE
      I
   1. ********  (      3)
      I
      I
   2. ********  (      3)
      I
      I
   3. ***************************  (      11)
      I
      I
   4. *************************************  (     15)
      I
      I
   5. ***********  (      4)
      I
      I
   6. ********  (      3)
      I
      I
      I.........I.........I.........I.........I.........I
      0         4         8        12        16        20
      FREQUENCY
```

```
      HEALTH-B

CODE
      I
  1.  *** (      1)
      I
      I
  2.  ************* (      5)
      I
      I
  3.  **************************** (     11)
      I
      I
  4.  ************************************ (     14)
      I
      I
  5.  *********** (      4)
      I
      I
  6.  ****** (      2)
      I
      I
  7.  *** (      1)
      I
      I
  8.  *** (      1)
      I
      I
      I.........I.........I.........I.........I.........I
      0         4         8        12        16        20
      FREQUENCY
```

```
      HEALTH-C

 CODE
      I
   1. *********** (       4)
      I
      I
   2. **************************** (      11)
      I
      I
   3. **************************** (      11)
      I
      I
   4. *********************** (       9)
      I
      I
   5. ******** (       3)
      I
      I
   7. *** (       1)
      I
      I
      I.........I.........I.........I.........I.........I
      0         4         8        12        16        2.
      FREQUENCY
```

HOUSING-A

```
CODE
     I
  1. ***** (        1)
     I
     I
  2. ********************************************* (        9)
     I
     I
  3. ******************** (        4)
     I
     I
  4. ****************************** (        6)
     I
     I
  5. ****************************** (        6)
     I
     I
  6. ********************************************* (        9)
     I
     I
  8. *************** (        3)
     I
     I
 11. ***** (        1)
     I
     I
     I.........I.........I.........I.........I.........I
     0         2         4         6         8        10
     FREQUENCY
```

```
          HOUSING-C

      CODE
          I
       1. ************************ (      9)
          I
          I
       2. **************************************** (      15)
          I
          I
       3. *************************** (      10)
          I
          I
       4. *********** (      4)
          I
          I
       5. *** (      1)
          I
          I
          I.........I.........I.........I.........I.........I
          0         4         8         12        16        20
          FREQUENCY
```

POLLUTION-A

```
CODE
      I
   1. *** (       1)
      I
      I
   2. ******** (        3)
      I
      I
   3. ****** (        2)
      I
      I
   4. *********** (        4)
      I
      I
   5. ************* (        5)
      I
      I
   6. ************************************** (        15)
      I
      I
   7. *** (       1)
      I
      I
   8. *********** (        4)
      I
      I
  10. ****** (        2)
      I
      I
  13. *** (       1)
      I
      I
      I.........I.........I.........I.........I.........I
      0         4         8         12        16        20
      FREQUENCY
```

```
          POLLUTION-C

      CODE
          I
       1. ****************** (       7)
          I
          I
       2. ******************** (       8)
          I
          I
       3. ********************************* (       13)
          I
          I
       4. ****************** (       7)
          I
          I
       5. ****** (       2)
          I
          I
       6. ****** (       2)
          I
          I
          I.........I.........I.........I.........I.........I
          0         4         8        12        16        20
          FREQUENCY
```

POVERTY-R

```
CODE
    I
 1. ********** (       4)
    I
    I
 2. ********************************************* (      18)
    I
    I
 3. ************************* (      10)
    I
    I
 4. ************ (       5)
    I
    I
 5. *** (       1)
    I
    I
 6. *** (       1)
    I
    I
    I.........I.........I.........I.........I.........I
    0         4         8        12        16        20
    FREQUENCY
```

POVERTY-C

```
CODE
        I
  1.    ************************************** (      15)
        I
        I
  2.    ******************************** (      13)
        I
        I
  3.    ******************** (       8)
        I
        I
  4.    *** (       1)
        I
        I
  5.    *** (       1)
        I
        I
        I.........I.........I.........I.........I.........I
        0         4         8        12        16        20
        FREQUENCY
```

```
TRANSPORTATION-B

CODE
     I
  1. ******************** (       4)
     I
     I
  2. **************************************** (       8)
     I
     I
  3. ************************************************** (      10)
     I
     I
  4. ********************************************* (       9)
     I
     I
  5. *************** (       3)
     I
     I
  6. ******************** (       4)
     I
     I
  7. ***** (       1)
     I
     I
     I.........I.........I.........I.........I.........I
     0         2         4         6         8        10
     FREQUENCY
```

```
        TRANSPORTATION-C

CODE
        I
   1.   ********************* (      8)
        I
        I
   2.   *********************************** (      14)
        I
        I
   3.   ****************** (      7)
        I
        I
   4.   ****************** (      7)
        I
        I
   5.   ****** (      2)
        I
        I
   6.   *** (      1)
        I
        I
        I.........I.........I.........I.........I.........I
        0         4         8         12        16        20
        FREQUENCY
```

UNEMPLOYMENT-A

```
CODE
      I
  2.  *** (       1)
      I
      I
  3.  ****** (       2)
      I
      I
  4.  ****** (       2)
      I
      I
  5.  ********************* (       7)
      I
      I
  6.  ************************************ (      12)
      I
      I
  7.  *** (       1)
      I
      I
  8.  ********************* (       7)
      I
      I
  9.  *** (       1)
      I
      I
 10.  ************ (       4)
      I
      I
 12.  ****** (       2)
      I
      I
      I.........I.........I.........I.........I.........I
      0         4         8        12        16        20
      FREQUENCY
```

UNEMPLOYMENT-B

```
CODE
     I
  1. ****** (      1)
     I
     I
  2. ****************************** (      6)
     I
     I
  3. ********************************************* (      9)
     I
     I
  4. ********************************************* (      9)
     I
     I
  5. ************************************************** (     10)
     I
     I
  6. ****** (      1)
     I
     I
  8. **************** (      3)
     I
     I
     I.........I.........I.........I.........I.........I
     0         2         4         6         8        10
     FREQUENCY
```

```
      UNEMPLOYMENT-C

CODE
      I
   1. ************* (      5)
      I
      I
   2. ****************** (      7)
      I
      I
   3. ****************************** (     12)
      I
      I
   4. **************************** (     11)
      I
      I
   5. *** (      1)
      I
      I
   6. ******** (      3)
      I
      I
      I.........I.........I.........I.........I.........I
      0         4         8        12        16        20
      FREQUENCY
```

Vita

David R. Unger was born in Tacoma, Washington, on April 5, 1951. He graduated from high school in June 1969 and entered Washington State University the following fall. Upon his graduation in 1973, he was awarded a Bachelor of Science degree in physics and a commission as a second lieutenant in the United States Air Force.

After completing the Communications-Electronics Maintenance Officer course at Keesler Air Force Base, Mississippi, he was assigned to the 3rd Mobile Communications Group at Tinker Air Force Base, Oklahoma. From 1974 to 1976, he was responsible for the maintenance of several types of tactical wideband communcations sytems.

In 1976, he was transferred to Headquarters Southern Communications Area, Oklahoma City Air Force Station, Oklahoma. There he served first as Officer-in-Charge and later as Director of the Navigational Aids Communications Management Office. It was from this assignment that he entered the Air Force Institute of Technology, Graduate Systems Management program, in June 1977.

He is married to the former Elizabeth D. Bullock of Spanaway, Washington. They have two sons, Christopher and Michael.

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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER AFIT/GSM/SM/78S-23	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) AN INVESTIGATION OF A HUMAN INFORMATION PROCESSING MODEL FOR DECISION MAKING		5. TYPE OF REPORT & PERIOD COVERED MS Thesis
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) David R. Unger Capt USAF		8. CONTRACT OR GRANT NUMBER(s)
9. PERFORMING ORGANIZATION NAME AND ADDRESS		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS		12. REPORT DATE September 1978
		13. NUMBER OF PAGES 119
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

Approved for public release; IAW AFR 190-17

JOSEPH P. HIPPS, Major, USAF OCT 10 1978
Director of Information

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Environmental Complexity
Fractional Factorial Design
Human Information Processing
Integrative Complexity
Policy Capturing
Regression Analysis

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This research examined information overload in decision makers by means of a human information processing model developed by Schroder, Driver, and Streufert. That model provided that the ability of an individual to integrate data into a decision varied in a curvilinear fashion with the complexity of the information environment. Information processing capacity was hypothesized to increase up to a certain optimum level and then decrease, marking the onset of information overload.

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A policy-capturing exercise was employed to measure the amount of information processed for three different levels of information availability. Subjects were given sets of four, six, or eight national problem areas along with hypothetical priorities that the federal government was said to attach to those problems. The subjects indicated their levels of agreement or disagreement with each set of priorities. Regression analysis was then used to discover how many of the available problem areas contributed significantly to the three sets of decisions. The information utilization patterns were compared to the predictions of the model.

About 21 percent of the sample displayed the type of pattern predicted by the model. Another 29 percent consistently used more information as more became available. A discriminant analysis conclusively classified the remaining subjects into one of the two groups: one for which information overload occurred and one for which it did not. The amount of information processed by both groups was identical at the four- and six-factor input levels, differing only after overload occurred.